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TO STUDY THE AUTOMATION OF THE

INTERPRETATION OF MONITORED

DRILL PERFORMANCE

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FINAL REPORT

TO: N.B. COAL LIMITED

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1.0 SOMMAIRE:

Ce rapport comprend les résultats finaux du projet de recherche exécuté par CCARM pour la compagnie New Brunswick Coal. La durée du projet était de huit mois, soit de mars 1991 à octobre 1991 inclusivement. Ce projet porte sur la recherche de méthodes d'automatisation de l'interprétation des performances d'une foreuse en utilisant des techniques de reconnaissances de patron. L'enregistrement et le traitement de données, obtenues lors de forage de production avec une foreuse Marion M5 à la mine Minto, a servi de base de données pour la recherche.

Le but initial du projet était de déterminer des algorithmes de reconnaissance adéquat basés sur les données recueillies par CCARM-McGill en juin 1990. Cependant, l'enregistrement et le traitement de données additionnelles ont dû être effectués à la mine Minto. Cet ajout de données a été fait à l'aide d'un system Stratalogger Plus de Thunderbird Pacifique, jumelé à une enregistreuse analogue de type DAT.

Les objectifs initiaux du projet de recherche étaient comme suit:

- de déterminer la base mathématique pour *l'automatisation* de l'interpètation des réponses enregistrées d'une foreuse, et

- de spécifier les composantes nécessaires selon la méthode d'automatisation choisie pour effectuer le suivi d'une foreuse.

L'évaluation du system Stratalogger Plus de Thunderbird Pacific, installé au paravant sur une foreuse à la mine, a été ajoutée aux objectifs initiaux du projet.

Les méthodes de sautage présentement utilisées à la mine ne font pas appel à la segmentation des charges explosives, même si la présence de pélites ou de schists argileux friables est évidante. Des coûts de sautage élevés, une mauvaise fragmentation et des niveau de vibrations élevés sont les effets de cette méthode de dynamitage. Le aniveau de vibration est de grande importance étant donné que des quartiers résidentiels se trouvent à proximité de la mine. C'est pourquoi un but plus précis a été déterminer, soit la faisabilité de la modification de l'emplacement des charges explosives basée sur la résistance au sautage déterminée par l'enregistrement et le traitement de données obtenues lors du suivi d'une foreuse.

Le résultat a donc été de former une base selon laquelle un programme (ainsi que les composantes physiques) peut être développé pour permettre l'analyse automatique et l'interprétation systematique des performances d'une foreuse. Cette aptitude permettrait de déterminer avec précision le type, la profondeur et l'épaisseur de chaque couche, que ce soit des rejets (pélites rouges et grès) ou du charbon, et ce d'un trou à l'autre, uniquement basé sur les différentes réponses d'une foreuse.

Les différentes étapes du projet ont été: l'acquisition de données à la mine, l'analyse des données et la mise à l'essai. Ces points sont élaborés dans les chapitres suivants.

1.0 EXECUTIVE SUMMARY:

This document reports on the final results of a research project between CCARM-McGill and New Brunswick Coal. This 8 month project, which commenced on March 1, 1991 and terminated October 31, 1991, proposed an approach to investigate methods to automate the interpretation of drill performance data using pattern recognition techniques. The data needed for this work, was to be acquired during routine production blasthole drilling from an on-board monitoring system on a Marion M5 drill at the Minto mine, New Brunswick.

The proposed research to define suitable pattern recognition algorithms for the NB Coal site, was initially based on drill data acquired by CCARM-McGill from research projects dating back to June 1990. However, additional field monitoring at the Minto mine, using the Thunderbird Pacific Stratalogger Plus system and a DAT analog recorder, was also to form critical parts of the research.

The initial objectives outlined for the research were to:

- define the mathematical basis for *automating* the interpretation of monitored drill performance parameters, and,

- specify the hardware requirements for a drill monitoring system which would incorporate the defined automated recognition capability.

An extension of this objective was the evaluation, in light of the recognition application, of the Thunderbird Pacific Stratalogger Plus system previously installed on a drill at the mine.

Currently, the blasting standards at the mine do not deck within the blastholes, even in the presence of obvious friable and weathered mudstone/shale horizons. This approach clearly results in excessive powder costs, poor fragmentation and high ground vibrations. This latter result of the blasts was of considerable and immediate concern to the mine, as it is surrounded by residential areas. Therefore, a more specific objective of the research, was to determine the feasibility of using the monitored drill responses to identify of zones of varying "blastability" to enable more precise explosive placement.

The final results of the work were to thus form the foundation upon which software (and hardware) to enable the automated processing and interpretation of drill performance data could be developed. This capability would permit the type, depth and thickness of the waste (red mudstones and sandstones) and coal horizons to be accurately identified from borehole

to borehole, based solely on the monitored drilling performance variable responses. A developed and implemented drill monitoring system, could form the basis of a reliable and robust blast engineering and production tool for open-pit mining operations.

The research was undertaken in several stages involving field drill performance data acquisition, analysis and experimentation. These areas will be covered in greater detail in subsequent sections.

2.0 INTRODUCTION:

Over the past 3 years, CCARM-McGill has been conducting research with both mining companies and manufacturers to develop means by which bench geology can be automatically recognize from monitored drill data. From these studies, and more recently in the current project with NB Coal, it has been determined that the signals of drill head vibration, torque and penetration rate provide the best results using the developed techniques. These signals can be readily obtained from any of the typical open-pit blasthole drills using appropriate sensors installed at the proper locations.

The monitored signals from the drill are subsequently processed using techniques similar to those utilized in the fields of speech and handwritten character recognition. Pattern recognition techniques have been under development for over thirty years in a wide variety of applications, for example, seismic trace interpretation. In light of these efforts, it was thought appropriate to draw upon the wealth of techniques already available in the literature. One of these techniques involves encapsulating spectral information by means of autoregressive (AR) coefficients, a conventional method used in many signal recognition applications. Two standard classifiers, the k-nearest neighbour decision rule (KNN) and the artificial neural network (ANN), are commonly used methods and are also being investigated for use in the drilling application. The KNN is a computationally intensive method often used for comparative purposes, while research into ANN's has enjoyed a certain renaissance since the early eighties resulting in this method becoming a powerful and versatile means of discrimination.The use of context, that is the use of information not pertaining specifically to the data, is achieved via the application of Hidden Markov Models (HMM), a technique broadly implemented in the field of speech recognition. Experiments were conducted in the current research project to evaluate the relative merit of each of these approaches. The recognition techniques and results obtained from their use will be explained in greater detail in subsequent sections.

Several field studies have been conducted in open pit coal mines to provide the base data for this research. These studies involved the monitoring of up to 14 variables on both

electric and hydraulic rotary blasthole drills using 270 (10 5/8) to 311 millimeter (12 1/4 inch) diameter tricone bits, to obtain in excess of 6000 meters (20000 feet) of production drilling data. This early work was motivated by the need of surface mines to maximize the quality of geological information while minimizing the cost or effort of obtaining such data through traditional means. In addition, the approach of extracting geological information from monitored machine performance data was attractive in that the holes had to be drilled anyway for blasting purposes. The techniques presently used in most surface mining operations to determine bench lithology is by combining the information from exploration boreholes, drillers' logs, drill cuttings, and in some mines the geophysical logging of production boreholes. Structural complexities within the bench often render information from the first source incomplete, while the second two sources provide information that has been found to be sometimes imprecise and unreliable i.e. operator dependent. Geophysical logging, on the other hand is generally costly and entails a considerable amount of time to derive a complete and accurate interpretation. In addition, numerous factors can influence the quality and validity of the geophysical traces (Matuszak, 1972). Preliminary results from these studies showed that logs of torque, pulldown pressure, rotary speed and penetration rate to depth gave a clear indication of the changing lithology as determined from core and geophysical logging (Peck, 1989).

The objective of the research which followed was to establish the criteria for obtaining reliable lithological information automatically from drill variable responses in a cost and time efficient manner. Using the drill data obtained from these field studies, experiments were conducted to select and subsequently evaluate the relative merit of each of the recognition techniques. The results of the work made it apparent that once the initial capital costs of hardware installation were incurred, reliable geological data could be furnished to the mine on a borehole by borehole basis at little or no additional cost. Thus, an implemented rock recognition system would provide, at nominal cost, valuable information regarding the bench geology which could be used for designing blasts towards reducing dilution and explosive costs, improving fragmentation and facilitating short and long-term planning (Peck et.al., 1991).

A similar approach as in these earlier studies was followed for the NB Coal project. The details of the different tasks of this work are described in detail in subsequent sections. Section 3.0 will first provide a comprehensive review of the pattern recognition techniques used in the current work. Section 4.0 will review the framework of the data acquisition hardware, the scope of the field tests conducted at the mine and the relationship between drill performance variables and geology. In addition, this section will discuss preliminary results from an analysis of the field data. Section 5.0 will examine in more detail the experimental procedures followed to evaluate the performance of the different recognition techniques. Section 6.0 will render pertinent conclusions based on the results obtained from

the data analysis and in light of the project objectives, and will also examine directions for future work based on what has been established in the current research work. The possible benefits of drill monitoring in open-pit coal mines is also discussed in this section.

3.0 REVIEW OF RECOGNITION TECHNIQUES:

3.1 Overview:

Classical pattern recognition consists of two consecutive components: feature extraction and classification. Given two or more classes - or in the present context rock types - and some data which may be used to distinguish between them, the first step involves quantifying the characteristics of the data set which allow for discrimination. This results in the formation of a feature vector which describes each of the entities (depth intervals) to be recognized. Classification refers to the method by which the vectors, or patterns, are assigned to a class. All classifiers must first be trained using known or labelled patterns This entails partitioning the pattern space into regions corresponding to class. A decision rule then designates subsequent unknown patterns to the classes in whose regions the patterns lie.

A multitude of ways have been developed to establish these partitions, ranging from linear discriminant functions to more complex strategies involving context. Two such methods were considered for the research: the k-nearest-neighbor decision rule (KNN) and artificial neural nets (ANNs). The merit of another "standard" method, the maximum likelihood estimation (MLE) or Bayes decision rule, has been previously explored yet was demonstrated to render inferior results with respect to the KNN rule (Pollitt, 1990). This was shown to be due to the fact that the class-conditional distributions of the rock types do not conform to a Gaussian (or any other "nice") fit, a condition which is essential for this parametric approach.

Feature extraction schemes previously considered by CCARM-McGill had been rather crude, in which the DC values of each of the responses were simply used as components in the feature vector. In doing so, information contained in the shapes of the signals was summarily disregarded. This seemed wasteful, especially in light of the fact that many applications, for example, speech or seismic, depend solely on shape for their discriminating capabilities. One popular way by which to capitalize on such spectral information is by means of a signal's autoregressive (AR) coefficients.

The use of context in recognition schemes has proven beneficial in many different applications (Toussaint, 1978) and it would appear that such information exists to be

exploited to identify strata. This is easily borne out by the fact that it is much easier for a geologist to log boreholes in conjunction with one another as opposed to logging them in independently. No published techniques will currently accommodate this task and thus a new algorithm, CONFORM, was developed to this end.

An overview of this technique, along with the classification methods mentioned above, are reviewed in the following subsections. The discussion of AR coefficients generally follows that given in Kay and Marple (1981) while the overview of ANNs is primarily drawn from Lippman (1987) and Hertz et.al. (1991).

3.2 AR Feature Extraction

An autoregressive model is one in which each term in a data sequence $\{x_n\}$ is expressed as a linear regression of the past terms plus an error term:

$$x_n = -\sum_{k=1}^{p} a_k \, x_{n-k} + n_n \qquad 3.1$$

where p is the order of the model or number of poles. The AR parameters $\{a_k\}$ are also known as Linear Predictive Coefficients (LPCs) in that, from the data sequence $\{x_0 \ldots x_{n-1}\}$ the model can predict term x_n.

This formulation defines a linear filter whose transfer function is the rational expression of the z-transform of the output sequence over that of the input sequence:

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sigma^2}{1 + \sum_{k=1}^{p} a_k \, z^{-k}} \qquad 3.2$$

where r^2 may be seen as the residual error or equivalently as the power not accounted for by the model. Given a finite data record, the set $\{a_k\}$ is found to specify this filter such that, when driven by white noise, it will produce the most random output sequence whose autocorrelation sequence matches that of the original data record. The system's frequency response will be the flattest of all spectra satisfying the same constraint. Consequently, spectral estimation by this method is known as Maximum Entropy Spectral Estimation. The rationale behind this approach is that it defines the linear model which imposes the fewest constraints on the unknown time series (of which one only has a small segment) thereby minimizing the resulting model's bias.

The are many different ways in which to calculate the set $\{a_k\}$. Some of these operate on the record's autocorrelation sequence while others operate directly on the data itself. For the purposes of this experiment, the algorithm by Burg (1967) was implemented. This arguably most popular technique is of the latter group and works by minimizing the forward and backward prediction error energies subject to a constraint which ensures a stable filter. Recursive by nature, the Burg algorithm successively generates the parameters for a model of a particular order from those for the model whose order is one less. Its algorithmic complexity is of order O(Pn).

This procedure thus renders p+1 (p coefficients and gain term) 'pieces' of information. If these were to be incorporated into a pattern vector in a straightforward manner, the Itakura-Saiko distance measure would have to be employed in order to appropriately discriminate between two respective patterns. This is more computationally involved and has been shown to be less effective than the conventional Euclidian measure (Basseville, 1989). Such a distance representation may be used only when comparing the log-spectra or cepstra for two records. These are derived from the AR parameters as follows:

$$c_n = -a_n - \sum_{k=1}^{n-1} \frac{k}{n} c_k a_{n-k} \quad , \quad 1<n\leq p \qquad 3.3$$

with

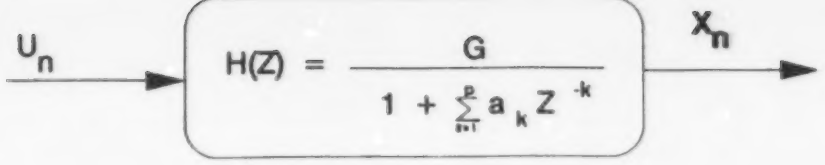
$$c_0 = \log\sigma^2 \quad and \quad c_1 = -a_1 \qquad 3.4$$

The use of cepstral coefficients also allows us to easily append the DC response values to the feature vector without any explicit modification of the decision rule.

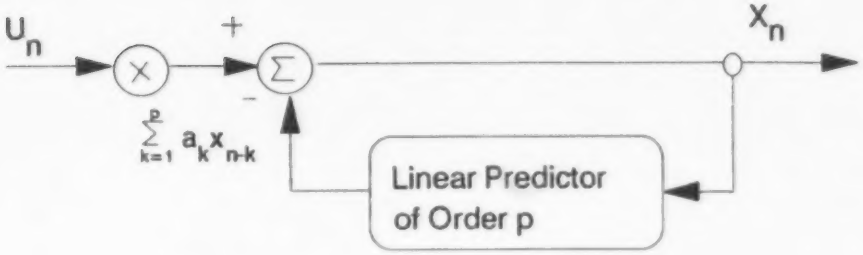
Figure 3.1 illustrates a generalized schematic of this technique.

3.3 KNN-Decision Rule

The nearest-neighbor (NN) decision rule is conceptually quite simple, in which an unknown pattern **x** is assigned to the class of its nearest-neighbor in the training set. The decision boundary in this case is defined by the set of hyperplanes common to Voronoi regions of differing class, see figure 3.2.
The KNN rule extends this principle and assigns the pattern to the class which is most heavily represented among the pattern's k nearest neighbors. This is generally more robust in that any noise present in the training set will tend to be overcome by the prevailing



Frequency domain representation



Time domain representation

Figure 3.1 - Generalized Schematic of the AR Feature Extraction Technique

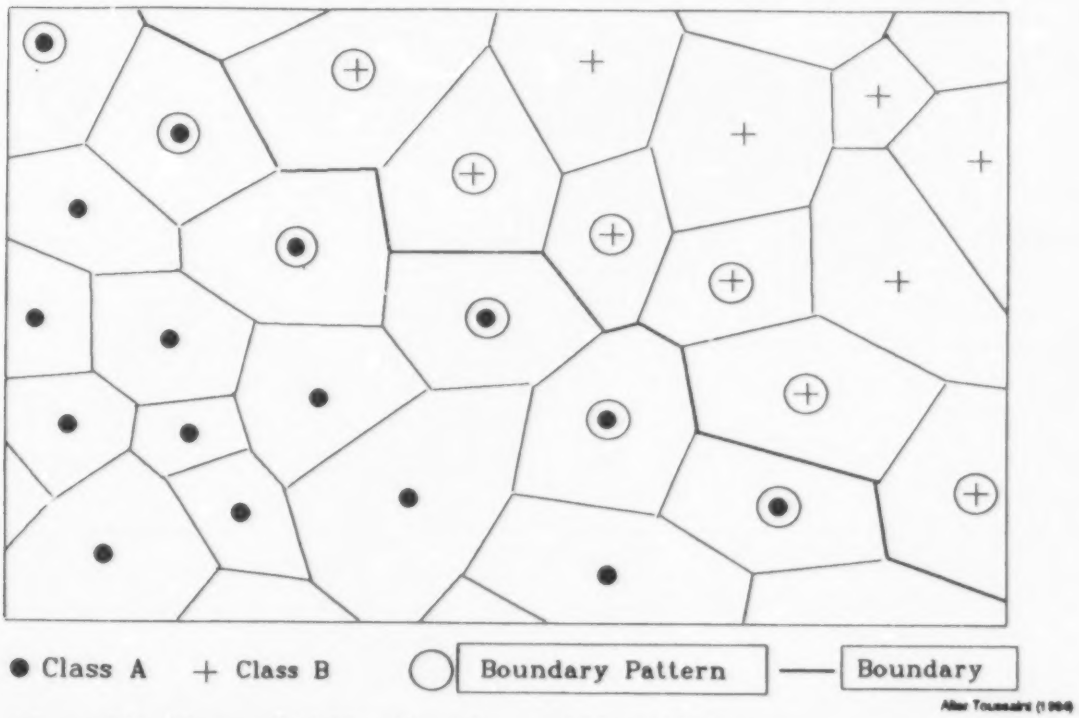


Figure 3.2 - Nearest Neighbor Boundary and Vornoi Diagram

trend of the class distribution if several of the patterns in the vicinity of the query vector are examined.

The merit of this technique is that no knowledge of the nature of the class distributions is needed *a priori*. Furthermore, it has been shown analytically that with sufficient training data the upper bound of the error rate is limited to twice the Baye's (or optimal) error rate (Duda and Hart, 1973). The drawbacks of the KNN rule relate to its implementation, where the training set must be saved and classification involves comparison with each of its member patterns. While some tree-based search algorithms have been devised to reduce the access time (Friedman et.al., 1977) and techniques from the field of computational geometry developed to eliminate superfluous patterns from the training set (Toussaint et.al., 1984), the burden of the space-time requirements are prohibitive for most applications. A KNN classifier is used here only for the purposes of comparison with a method that is considerably more attractive in terms of implementation.

3.4 Artificial Neural Nets

Artificial neural nets can be viewed as another non-parametric estimation technique. A network is composed of simple computational units linked together by connections of varying weight. Many different architectures - the ways in which the units are connected - have been developed, but for the purposes of the current experiments only fully-connected, feed-forward networks were considered. This implies that units are organized in layers and each unit of one layer is connected to each unit in the subsequent layer. Connected to the first layer of a network are the inputs which for recognition applications, consist of the components of the feature vector. Similarly, each unit in the last or output layer corresponds to a class, while any layers in between are referred to as hidden layers, see figure 3.3.

Classification is achieved by first presenting the network with an input x; unit j in the subsequent layer then emits an output y_j according to:

$$y_j = g(h_j) = g(\sum_k w_{jk} x_k) \qquad 3.5$$

where w_{jk} is the connection weight between unit j and component k of the pattern vector; g(h), the activation function, ensures the output remains within a given range. Among such functions is the sigmoid function,

$$g(h) = \frac{1}{1 + exp(-2h)} \qquad 3.6$$

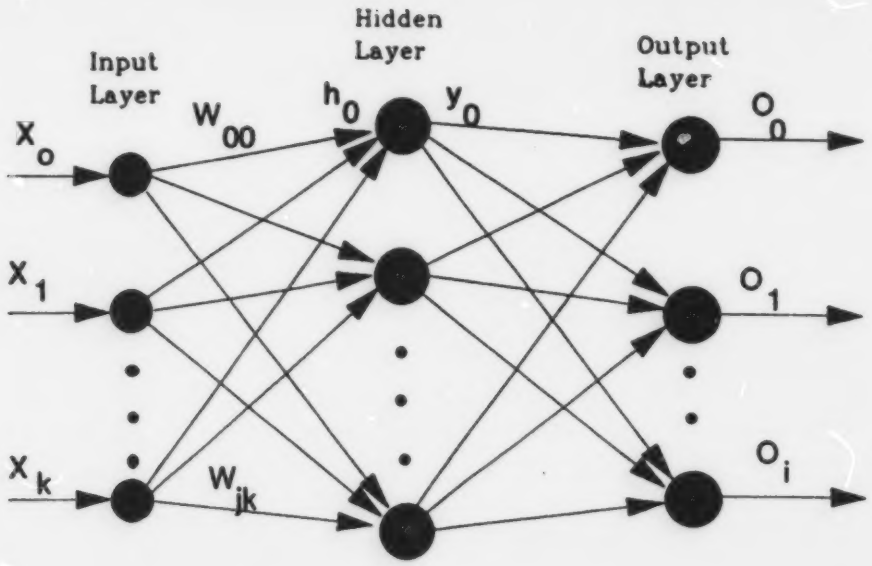


Figure 3.3 - Schematic of Artificial Neural Nets (ANNs)

which limits the output to the interval [0,1]. If the net consists of more than one layer, the second layer then treats the outputs of the first layer in the same manner the first layer treated the inputs and so on until the output layer is reached. The pattern is then assigned to the class whose corresponding unit in the output layer emits the highest value.

Training involves finding the appropriate set of weights, accomplished by means of the back-propagation algorithm. The procedure works by passing the labelled patterns through the net and after each adjusting the weights according to how 'correct' the output was,

$$w_{jk}\ (t+1) = w_{jk}\ (t) + \eta\ \delta_j\ x_k \qquad 3.7$$

where g is known as the gain or learning rate, x_k is the output from unit k (or input) and d_j is an error term found by taking the derivative of a cost function (which measures how 'correct' the classification was) with respect to each of the h_j's of the previous iteration. If unit j is within an output layer the error term works out to,

$$\delta_j = y_j\ (1- y_j)\ (d_j - y_j) \qquad 3.8$$

where y_j is the actual output of unit j and d_j is the desired output of unit j. The latter is usually set to 1 for the unit associated with the class of the training pattern and 0 for the others. If unit j is within a hidden layer then,

$$\delta_j = y_j(1- y_j) \sum_k \delta_k w_{jk} \qquad 3.9$$

The sum in eq. 3.9 is over all units in subsequent layers and it is in this sense that the errors are 'back-propagated'.

If a single-layer net has only one output and the activation function is a hard limiting non-linearity (g(h) = 1, h > 0, g(h) = -1, h < 0), it is easy to see that the n-dimensional pattern space is partioned into two regions by a hyperplane. This dividing hyperplane in such an architecture (the perceptron; Minsky and Papert, 1969), is orthogonal to the weight vector. Adding another layer allows for convex decision regions while yet another provides for arbitrary partitions whose complexities are limited only by the number of units. Replacing the above activation function with a sigmoidal function renders class boundaries that are continuous and as such difficult to analyze.

3.5 The Use of Context in Recognition

The means by which context is incorporated into the lithological recognition process primarily consists of established techniques which are reviewed below. Following this, the necessary modifications to these techniques including the rationale, are discussed in terms of the current rock recognition application.

3.5.1 Symbol String Recognition

Suppose we are given a sequence V of symbols of length N which are to be used to identify a corresponding sequence of labels, H, each belonging to 1 of M classes:

$$\begin{aligned} V &= (v_0, \ldots, v_k, \ldots v_N) \\ \Theta &= (\theta_0, \ldots, \theta_k, \ldots, \theta_N) \end{aligned} \qquad 3.10$$

The most likely sequence of symbols are those which maximize the posterior probability. Using Baye's rule we have

$$P(\theta_0, \ldots, \theta_N | v_0, \ldots, v_N) = \frac{P(v_0, \ldots, v_N | \theta_0, \ldots, \theta_N)\ P(\theta_0, \ldots, \theta_N)}{P(v_0, \ldots, v_N)} \qquad 3.11$$

To avoid the complexity of computing 3.11 directly, we assume that the symbol string is generated by a first-order Markov source; that is,

$$P(\theta_k|\theta_{k-1}, \ldots, \theta_0) = P(\theta_k|\theta_{k-1}) \qquad 3.12$$

This implies that the only pertinent information that can be obtained from the history of symbols seen-so-far is contained in the previous symbol. The probability on the left-hand side of 3.12 is known as the state transition probability. Thus the symbol sequence probability can be collapsed into,

$$P(\theta_0, \ldots, \theta_N) = P(\theta_0) \prod_{k=1}^{N} P(\theta_k|\theta_{k-1}) \qquad 3.13$$

Things can be further simplified by assuming the process is memoryless

$$P(v_1, \ldots, v_N|\theta_1, \ldots, \theta_N) = \prod_{k=1}^{N} P(v_k|\theta_k) \qquad 3.14$$

Substituting 3.13 and 3.14 into 3.11 gives

$$P(\theta_0, \ldots, \theta_N|v_0, \ldots, v_N) = \frac{P(\theta_0) \prod_{k=1}^{N} P(v_k|\theta_k)\ P(\theta_k|\theta_{k-1})}{P(v_0, \ldots, v_n)} \qquad 3.15$$

The symbol sequence probability is independent of class and can thus be disregarded; doing so and taking the logarithm leaves us the function G(V) to be maximized:

$$G(V) = \log P(\theta_0) + \sum_{k=1}^{N} \log P(v_k|\theta_k) + \log P(\theta_k|\theta_{k-1}) \qquad 3.16$$

The sequence of labels which maximize G(V) is found by a procedure known as the Viterbi algorithm. Before further explication the state transition and symbol probabilities are respectively expressed more compactly as

$$P(\theta_k|\theta_{k-1}) = Pr\,(\theta_j \bullet k+1\,|\theta_i \bullet k) = a_{ij} \qquad 3.17$$

$$P(v_k|\theta_k) = Pr\,(v_q \bullet k\,|\theta_j \bullet k) = b_{jq} \qquad 3.18$$

The Viterbi works by finding the 'best' path through a trellis-like structure whose length is equal to the length of the observation sequence and whose width is determined by the number of states. $d_j(k)$ is defined as the relative probability of being in H_j after having seen k symbols. It can be computed recursively as

$$\delta_j(k) = \max_{1 \le i \le N} [\delta_i(k-1)\, a_{ij}] \qquad 3.19$$

The procedure is usually initialized by setting $d_j(k)$ = Pij, the initial probability distribution

and terminates by determining the most likely state at point N. Backtracking is enabled if at each point k the state which maximized $d_j(k)$ at the preceding point is stored. That is, the variable $w_j(k)$ is introduced such that

$$\Psi_j(k) = \underset{1 \le i \le N}{argmax}[\delta_i(k-1)a_{ij}] \qquad 3.20$$

In this way the optimal state sequence is recovered trivially by working back up the trellis.

The algorithm runs in $O(NM^2)$ time and takes O(NM) space.

3.5.2 Estimation of HMM Parameters

To exploit this routine for the application at hand two parameters must be estimated, namely, the state transition probabilities aij and the symbol probabilities b_{jq}. The latter are found by a conventional technique using vector quantization while the former are estimated in a novel fashion from adjacent boreholes. The rationale for this approach will be seen in due course.

3.5.2.1 Quantization

The first step in estimating the set of symbol probabilities is the generation of a set of codewords, each of which represents a region in the pattern space. Many algorithms exist to undertake this phase. The particular one by Gray, (1984) is used here, and is initialized with one codeword located at the centroid of the training set. This codeword is then 'split' into two with the resulting second located very close to the first. Each pattern in the training set is then assigned to one of the two codewords on a nearest-neighbor basis and the codewords are subsequently re-located to the centroid of the data assigned to it. This process is repeated, with the two being split into four etc., until the desired number of codewords is reached.

The symbol probabilities are easily found by counting on the last iteration, the number of times a pattern from a given class (state) is assigned to a particular codeword. More precisely,

$$b_{jq} = \frac{\gamma_j(q)}{\gamma_j} \qquad 3.21$$

where $c_j(q)$ is the number of times codeword q is assigned a pattern from class j and c_j is the total number of times a pattern from class j is seen.

The first step in this post-processing routine is thus to encode, that is to replace with the

nearest codeword in the codebook, each of the real-valued patterns in the boreholes being considered. In this way a set of symbol strings, with respective probabilities, is obtained.

3.5.2.2 Transition-Probability Estimation

The likelihood of state transitions for applications such as speech and hand-written character recognition are particular to a finite set of entities and can consequently be estimated off-line. For example, to find the probability of an 'h' following a 't' in the english language all one must do is consult a dictionary and count. Unfortunately, no such 'lithological' dictionaries exist, as depositional histories will vary greatly amongst different sites as well as within the confines of a given site. Structural complexities that may be present will also inhibit one's ability to estimate [a priori] the nature of the sequence. The other major difference between the rock recognition application and the more traditional ones is that it would seem appropriate for the present case, to have the state transition probability matrix vary with respect to position in the symbol string, i.e. as a function of depth. This approach becomes clear when confronted with a site like NB Coal where certain rock units are found at consistent depths.

Assuming that the set of boreholes R are drilled relatively close to each other in a structurally simple, sedimentary environment. In such a case, the sequence and respective thicknesses of the bedding in one borehole can be assumed to very closely match that of the others. If a 'good' estimate of the lithologies can be found for a given borehole, then this same estimate can be used to approximate the transitions in the adjacent boreholes. The 'good' estimate being proposed here is a statically classified lithology.

The stratigraphic simplicity envisioned above is rarely encountered in open-pit coal mines. Direct hole-to-hole correlation is almost always distorted by the dip of the bedding, the lateral and vertical pinching and swelling of individual units, faulting, folding or any combination thereof. Thus if transition probabilities for a given borehole are to be estimated from the approximated lithologies in nearby boreholes, a set of relationships must be found which maps depth intervals from one hole to the corresponding intervals of the others. This set should also include a NULL mapping; that is, an interval in one borehole may be deemed to be foreign with respect to those of another as may be the case when significant faulting is involved.

An algorithm by Sankoff and Kruskal (1983) which has been widely used for string comparison, phoneme recognition and the analysis of DNA sequences, can be used with a slight modification to generate this borehole mapping. Given two boreholes, r and r', if D_{ij} is defined as a measure of similarity or distance between interval j in r and interval i in r', then the problem reduces to finding the shortest path through the implied trellis. The

metric used here, D_{ij}, is the Euclidean distance of the respective means of the codewords over the intervals. The shortest path can be found with a traditional dynamic programming routine similar to the Viterbi algorithm. The recursion equation in this case is

$$\phi(r_i, \bar{r}_j) = \min \begin{cases} [\phi(r_i, \bar{r}_{j-1}) + \Delta_{i,j-1}] * \beta_{i,j-1} \\ [\phi(r_{i-1}, \bar{r}_{j-1}) + \Delta_{i-1,j-1}] * \beta_{i-1,j-1} \\ [\phi(r_{i-1}, \bar{r}_j) + \Delta_{i-1,j}] * \beta_{i-1,j} \end{cases} \qquad 3.22$$

where U performs the same task as d in [3.19]; ß is a factor which normalizes the paths with respect to length. Backtracking is likewise undertaken as in [3.20]. The best path coinciding with point (i,j) implies that the intervals at r_i and r_j' correspond to each other.

This routine differs from those previously published in that the best path is not constrained to start at (i=0,j=0) nor end at (i=N,j=N'). Instead, to allow for the NULL mapping mentioned above, the path may start or terminate W positions from either endpoint; intervals in a hole not spanned by the path can obviously have no correspondence.

The output of this procedure is thus a mapping $H_{rr'}(k)$, which, if not NULL, relates each point k in r to a point in r', and $a_{rr'}$ which is an indication of the overall similarity of the two holes.

The transition probabilities can now be estimated by

$$a_{ij}^{\bar{r}}(k) = \sum_{r \in R(\bar{r})} \alpha_{r\bar{r}} \frac{\sum_{\kappa \in R_{ij}^{r}(k)} \lambda_{ij}(\kappa)}{\sum_{\kappa \in R_{ij}^{r}(k)} \lambda_{i}(\kappa)} \qquad 3.23$$

where

$$\lambda_{ij} = \begin{cases} 1 & \text{if } \theta_j \bullet \kappa + 1,\ \theta_i \bullet \kappa \\ 0 & \text{otherwise} \end{cases} \qquad 3.24$$

and

$$\lambda_i = \begin{cases} 1 & \theta_i \bullet \kappa \\ 0 & \text{otherwise} \end{cases} \qquad 3.25$$

3.5.3 The Algorithm

The procedure required to process monitored drill performance data for the lithological recognition application can be summarized as follows:

1 - generate a quantized vector codebook and corresponding symbol probabilities and training data;

2 - both classify statically and quantize the patterns in a set of closely-spaced boreholes;

3 - for each of the boreholes in the set, estimate the state transition probabilities as a function of depth and, having obtained the necessary HMM parameters, apply the Viterbi algorithm.

Executing the above steps will result in a newly estimated lithology for each hole. If this procedure is effective once, it would seem intuitive to apply it iteratively using the set of lithologies generated by the last cycle to estimate the transition probabilities for the current.

The results of processing the drill data from NB Coal, using this approach, will be discussed in later sections of this report.

4.0 QUALITATIVE DATA ANALYSIS:

The aim of the proposed research was to find answers for many questions left unanswered from previous field work and those which were certain to arise during the current project, in order to define a reliable lithological recognition system approach. This process involved an initial phase of experimentation composed of two stages: data acquisition and data analysis using the defined recognition methods. The following sections describe the monitoring hardware used, the field tests conducted, the determined site geology and a preliminary examination of the relationships between the drill variable responses and the geology. Preliminary results using the recognition techniques are provided at the end of this discussion.

4.1 Data Acquisition:

Two field monitoring periods were conducted at the Minto mine in order to collect the necessary drill performance data. The variables which were considered of interest in this

study were torque, rotary speed, pulldown and bailing air pressures and penetration rate with respect to depth in the borehole. These variables were be available from the Stratalogger Plus system previously installed on the Marion M5 drill at the mine. Based on past CCARM-McGill drill monitoring experiences, drill head vibrations were also considered to be important. These vibrations, measured in up to 3 directions on the drill head in earlier field studies, had been shown to provide critical information regarding a change from soft to hard rock and vice versa. The necessary transducers to measure the vibrations were proposed to be installed on the drill and integrated with the Stratalogger Plus hardware. Towards this end, it was decided that the axial vibration signal would provide sufficient data for the project. This uniaxial vibration sensor was purchased by CCARM-McGill and installed in a protective case on the drill head assembly by RPC (Research and Productivity Council) of Fredericton, N.B.

The objective of the field monitoring was to collect data that was representative of how the drill responds under "normal" production conditions in which the operator was permitted to run the drill as he normally would ie. making adjustments to rotary speed and pulldown according to changing ground and bit conditions. "Normal" production conditions also implied that the drill data should be collected over the life of at least one bit. During the field monitoring periods, only 2 bits were used, each having already drilled approximately 10,000 to 12,000 feet. However, since bit footages of 20,000 to 30,000 feet are possible at the mine prior to failure, bit wear was not considered a complicating factor.

The bit utilized during field period #2, manufactured by Varel, was different than the one used in the first field period (Smith-Gruner). This difference in bit manufacturer could manifest itself in terms of the drill variable responses[1]. This aspect could only be resolved reliably by drilling parallel holes in the same bench geology using the different bits - this was not done in the current study. Due to the considerable variation in the bench geology at NB Coal, an evaluation of the performance of these different drill bits was considered to have only provided inconclusive results. While any differences in the monitored responses could provide for an interesting comparison of bit types and design on drill performance, it is thought that the distinction between the two data sets will render them mutually exclusive. Experimentation to evaluate particular aspects of recognition performance (such as, for example, the importance of vibration) will, therefore, have to be addressed within the scope of one data set or the other.

---

[1] - differences in the drilling variable responses were noted in earlier field studies by McGill. There, Varel and Smith bits were used to drill parallel blastholes. It was quite apparent that the Smith bit resulted in higher overall penetration rates, and produce higher levels of torque and vibration when drilling soft, shale/mudstone units. This could be related to the different rolling action and insert design of the Smith bit which possibly enhances the scraping/gouging mechanisms thus increasing the rate of penetration.

The monitoring was also planned to be undertaken across all shifts, to examine how much influence different operators had on the performance of the drill. In order to examine the influence of the operator adjustments to rotary speed and pulldown pressure on the recognition capability, the set-points for these variables were also monitored. Table 4.0 lists the drill variables monitored by both the Stratalogger Plus (Str+) and the DAT recorder (DAT) and the sensors used for their acquisition. The field tests were also to be conducted within as many (if present) different bench geologies at the site as possible.

By monitoring under these various sets of conditions, the objective was to determine the necessary requirements for software to reliably identify changing ground independent of these other factors.

The success of any recognition strategy was noted to be highly dependant on the quality of data used to develop the identification algorithms. This is primarily a function of the monitoring hardware being used, and thus, for comparative purposes, drill data was acquired by means of three different devices as shown in figure 4.0:

A. Thunderbird Pacific's Stratalogger Plus;

B. a 16 channel Digital Audio Tape (DAT) recorder;

C. a portable PC computer with a 16 channel analog to digital board installed.

4.2 Field Period #1:

An initial field monitoring period was undertaken at the NB Coal mine in Minto, New Brunswick during a 2 week period from May 5 to 17, 1991.

Based on discussions with the mine geologist (B.McLean) and available exploration logs, it was determined that the mine had exploitable coal seams of 30 to 46 centimeters thick overlain by 27 to 30 meters of overburden. Based on previous exploration data, the overburden was seen to consist of flat-lying conglomeritic and fine-grained massive sandstone units interbedded with weaker siltstone, mudstone and shale beds.

The drill monitored at the site was a Marion M5 electric rotary machine, drilling 311 mm diameter holes. A Stratalogger Plus drill monitor from Thunderbird Pacific had been previously installed for purposes of collecting production statistics. The pulldown pressure, bailing air pressure, rotary torque, rotary speed and optical encoder sensors from this monitor were also monitored in parallel by the CCARM-McGill data acquisition hardware (figure 4.0). The DAT recorder and portable PC computer with a 16 channel A/D card

Table 4.0 - List of Monitored Performance Variables on a Marion M5 Drill

Variable:	Sensor Type:	Str+	DAT	Location on Drill:
Depth	Potentiometer		*	Top of drill tower
Penetration Rate	Tachogenerator		*	*
	Optical Encoder	*	*	Hoist/chain sprocket
Pulldown Pressure	Pressure	*	*	In line to pulldown pressure gauge
Bailing Air Pressure	Pressure	*	*	In line to bailing air pressure gauge
Rotary Speed	Rotary motor voltage	*	*	Voltage in to motor
Rotary Torque	Rotary motor current	*	*	Armature current across motor shunt
Axial Vibration	Piezoelectric accelerometer		*	On rotary head assembly
RPM Setpoint	voltage		*	Signal from a rheostat on rotary control knob
Pulldown Setpoint	voltage		*	Signal from a rheostat on pulldown control knob

(Analog Devices) were interfaced to these sensors via a box designed and installed by RPC. Additionally, an accelerometer (IC Sensor) was installed on the rotary head to measure axial vibration. A position/velocity transducer (Rayelco) was also used to enable an evaluation of the optical encoder signal from the Stratalogger Plus hardware. The PC computer with the A/D card enabled on-line data digitization, permitting an immediate verification of the status of all the electronic equipment.

A total of 33, 27 to 30 meter deep blastholes were monitored during this period. These consisted of 5 groups of 6 to 7 boreholes (9 meters apart) each, where each group was

separated by up to 20 boreholes. The relatively large distances separating the boreholes is seen as providing for a calibration unbiased by proximity. Twenty-four of the monitored boreholes were also logged with a geophysical probe, to hopefully permit the accurate identification and segmentation of the bedding based on an interpretation of gamma, density and resistivity responses. Century Geophysical Corp., Calgary, were contracted to undertake geophysical logging of specified testholes. Figures 4.1 and 4.2 show the drill and geophysical logs with a preliminary geological interpretation, for two parallel monitored boreholes, NB 33 and NB 37.

In these figures, "shales" also include mudstones, "sandstones" include siltstones, and the "interbedded" units are made up of interbedded siltstones and mudstones. Also the variables illustrated are from left to right: gamma, density, rotary speed (rpm), rotary torque (amps), pulldown pressure (psi), vibration (relative units) and penetration rate (ft/h). The logs for resistivity are not shown as the monitored response was considered invalid for the NB Coal blastholes - water filled boreholes are required for a meaningful signal. Note that the scales for the drill variables have not been converted to their actual engineering units and therefore their absolute values are meaningless. However, it is apparent from these figures that the relative responses of these logs do reflect the changing rock types.

4.3 Field Period #2:

A second field monitoring period took place between the 19th and 23th of August, 1991. The duration of this period was shorter than anticipated due to technical failures of the accelerometer (vibration) and linear potentiometer (penetration rate and displacement) on the drill. These sensors were replaced/repaired by RPC, Fredericton. In addition, mechanical problems with the drill precluded any possibility of further data collection beyond August 23.

Regardless of these problems, data were obtained for an additional 16 monitored blastholes. The bench area monitored was beyond the zone of glacial till (a.k.a. red mud) where the stratigraphy was considerably different from that encountered during field period #1.

Further examination of the differences in bench lithology at the mine was also undertaken during this period. The highwall was scaled and samples taken at several intervals. This action clearly indicated the considerable variation of rock strengths present at the site. In some horizons, the sandstones could not be broken with a hammer, while in other areas, the mudstones crumbled when handled. No additional geophysical logging was undertaken during this period.

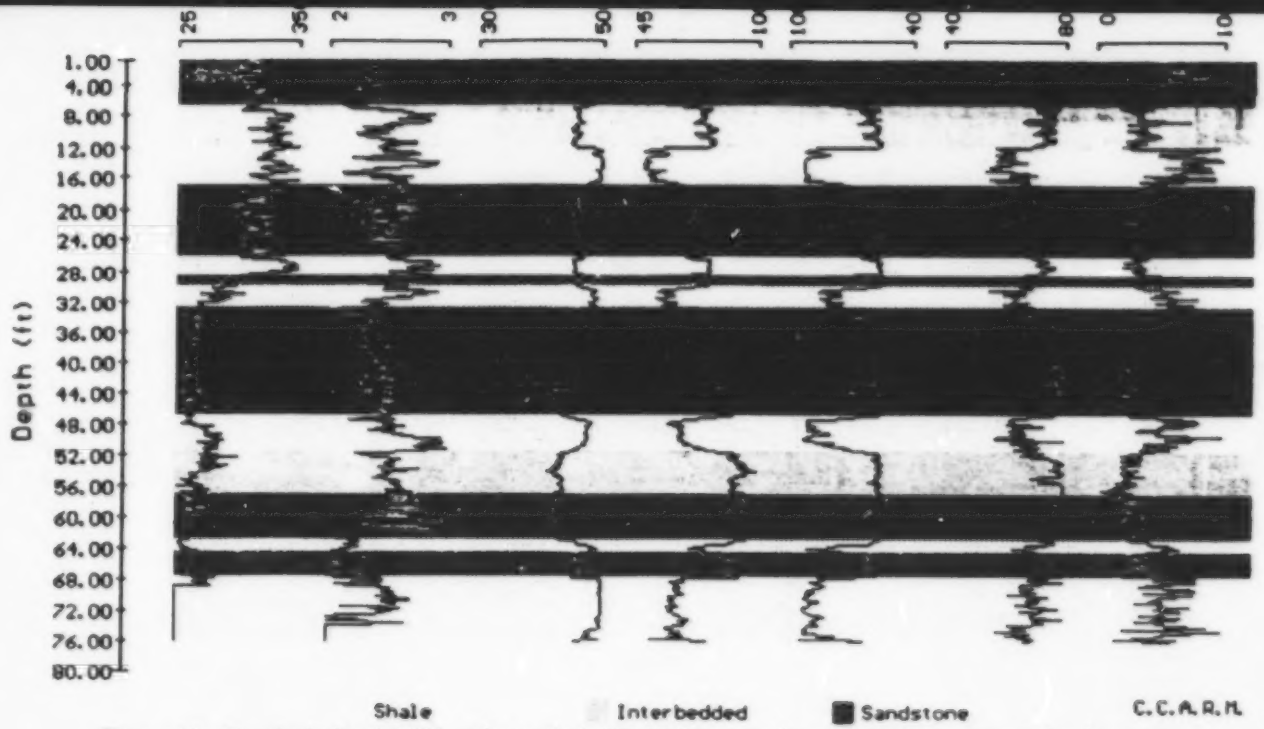


Figure 4.1 - Geophysical and drill logs for testhole NB-33; Logs are from left to right: gamma, density, rotary speed, torque, pulldown pressure, axial vibration and penetration rate.

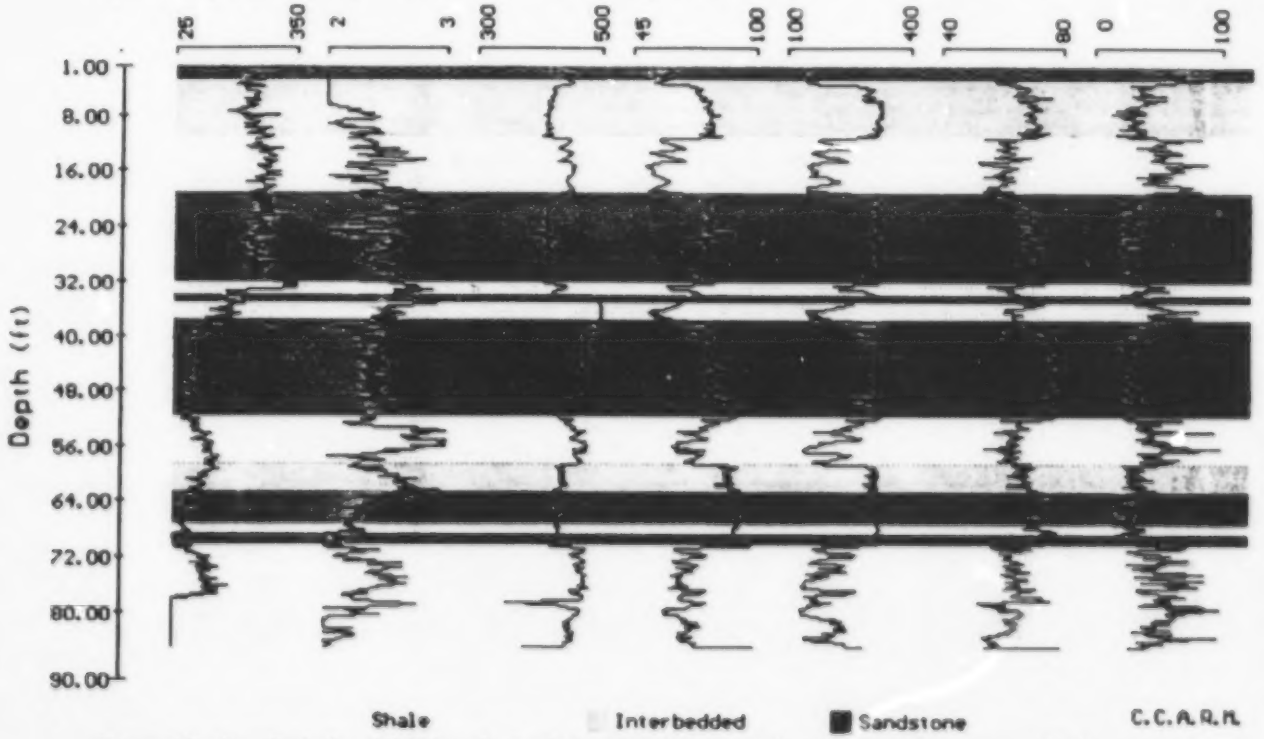


Figure 4.2 - Geophysical and drill logs for testhole NB-37; Logs are from left to right: gamma, density, rotary speed, torque, pulldown pressure, axial vibration and penetration rate.

4.4 Geological Investigations:

This section discusses an examination of the drilling parameter responses in terms of their relationship to both the different rock types and the influence of the operator. A discussion of the rock types - how they were defined, how they were characterized and how they distribute themselves at NB Coal is also provided. This examination was undertaken to provide the necessary knowledge-base for the design of experiments and give insight into the ensuing results in relation to understanding the machine-rock interaction.

4.4.1 Definition of Rock Types and Initial Labelling of Data:

At NB Coal, six rock types were defined in more detail as hard sandstone (HS), weathered sandstone (WS), mud/shale (MS), rehandle (RH), coal rock (CR) and coal (CL). These rock classes were determined and the drill performance data subsequently labelled on the basis of the geophysical logging, the drill parameter responses, exploration holes and bench mapping. The latter data source was obtained from a visual inspection of the cut (which included its traversal) and consultation with mine personnel.

Despite these geological investigations there still remained a degree of uncertainty by which the different rock units could be accurately defined. This aspect can be attributed to the gradational nature of the transitions from one rock type to another, for example, how was it possible to clearly define the siltstone partings when interbedded with mudstone/shale units? Also, if the siltstones contained a high clay content (ie. "muddy") how could these rocks be reliably distinguished from mudstones or shales having a high sand percent (ie."sandy"). Although these rock types are compositionally similar, their physical properties and thus the drill data responses would be different. Therefore, in some cases, the geophysical data did not indicate variation in rock type, yet the drill data showed some changes, the origin of which could not be determined.

Gamma logs can provide an indirect means of determining formation densities based on the response of the probe to changing concentrations of radioactive elements present in the rock units. The gamma ray logs, however, are sensitive to variations in the borehole diameter such as through caved zones, resulting in potentially inaccurate definition of coal and the various waste rocks. The resolution of gamma logs under ideal conditions and when the probe has been calibrated is approximately 6 inches. However, this precision diminishes with the presence of sandstone-mudstone units within the bench (Schwaetzer, 1965), as is the case at NB Coal. Density or neutron log data measurement, as for gamma logs, is also affected by several factors namely: changes in hole size, fluid saturation, porosity and lithology. Normally when neutron log responses are properly interpreted, a clear distinction of the various units of coal measures rocks is obtained. However, the resolution of the logs

can be reduced when certain borehole conditions, as outlined above, exist. The combined analysis of neutron and gamma logs should provide a better and more reliable interpretation of the geology (Matuszak, 1972), but it was apparent in the present case that neither log was very definitive in identifying interbedded units. Regardless of these problems in defining the bench geology in detail, it was possible, using the geophysical data to identify the location of massive sandstone and thick mudstone/shale zones. In those boreholes where they were encountered, coal and rehandle were also clearly discriminated by their very low gamma log responses.

In order to further define those zones transitional to the more pure end members for sandstone and mudstone/shale, another approach was adopted. This was based on an understanding of why drill parameter responses vary in different material types. At the fundamental level of the bit-rock interaction, it is apparent to see that different mechanisms are operating to excavate and thus penetrate rock depending on the physical properties of the material. In hard, homogeneous, clay-poor material, for example, massive sandstone, the drill, for a particular level of rotary speed and pulldown and no bit wear, will respond in a unique manner. This situation would be manifest by high and steady pulldown pressure, torque and vibration, with low rotary speeds and penetration rate. The high pulldown pressures and low rate of penetration indicate that impact-crushing failure mechanisms of rock are being generated at the bit-rock interface. When the bit impacts the hard sandstone, the inserts must overcome the compressive strength of the rock before penetration is possible. Through brittle failure, the inserts crush and penetrate the rock with the broken material (chips or cuttings) cleared as the bit cones rotate. The abrasive nature of the quartz-rich sandstones and the high pulldown pressures employed result in high torques and corresponding low rotary speeds.

Conversely, in softer materials eg. mudstones and shales, excavation of rock is via a scraping-gouging action of the bit inserts. Here the inserts penetrate their full length into these ductile rocks of low compressive strength. The bit rotation subsequently serves to impart a lateral load on the inserts in order to scrape and thus remove the penetrated material. The corresponding drill response is higher penetration rates, lower torques and vibrations (except in very sticky rocks where torque and vibration could increase due to bit balling), higher rotary speeds and a fluctuating pulldown pressure response. This latter response is due to the material excavation rates exceeding the loading rate of the bit[2] . The pressure in the pulldown hydraulic system thereby decreases, with these changes correlating to the occurrence of very soft rock or weak zones. Vibration responses are quite useful for discriminating hard versus soft rock, and it is clear that at "normal" levels of rotary speed and pulldown, vibration levels are highest in more brittle (strong) rocks. Here,

[2] ie. load on the bit is >>> compressive rock strength

the impact energy at the bit-rock interface is high, and is reflected and subsequently transmitted back up through the drill string to the rotary head. In more ductile rocks, the bit energy is attenuated by the plastic nature of the medium and thus less vibration is reflected or transmitted. An exception to this case is when drilling in sticky shales - bit balling can cause high vibrations to develop, due in part to the steel slapping the sides of the borehole. In this situation, the monitored axial vibration is primarily a component of a lateral vibration signal.

Using the above logic, the rock classes at NB Coal were further determined to a large extent on the known responses in drilling parameters to particular material properties. The most apparent advantage of this approach was in the distinction between hard sandstone and weathered (broken) sandstone which could not be differentiated by the geophysical logs.

From an analysis of the drill logs, it was clear that the stratigraphy varied significantly at the mine site. This variation was observed to occur over the span of a single borehole spacing even though there was little or no structural complexity. The diversity over distances of 300 feet (2-3 blasts) along the cut was considerable, with these observations clearly supported by figure 4.3 showing borehole NB45 and NB 32. These boreholes were drilled approximately 250 feet apart, and it is clear that the logs for NB 32 indicate thick, hard sandstone beds, while borehole NB 45 exhibits that the same units have thinned considerably. As well, the thin mudstone/shale units seen in hole NB 32 are much thicker when they are encountered in NB 45.

Despite the encountered stratigraphic variation, there were some geological features which remained relatively constant during the first field monitoring period. However, the second field period occurred north of the location of red mud units where the sequence is almost entirely foreign to that in the rest of the cut. This area constitutes a relatively small percentage of overall production and thus could be considered atypical for this site. In general, the stratigraphy is consistent in that rehandle is always at the top of the hole while the coal rock is always near the bottom. A very hard band of sandstone, though varying in thickness, was identified in each monitored hole at approximately half the bench height. As well, a thick mud/shale unit tends to be located at 70 to 90 feet in depth.
For recognition applications it is usually more advantageous to view the data in terms of scatterplots, whereby the relationships amongst the parameters and classes are more readily apparent. A scatterplot of vibration versus penetration rate is given in figure 4.4. where a weak, inverse correlation between these two parameters is indicated. While the separation between HS and WS is good, that between WS and MS and, to an even greater extent, MS and RH is rather unclear. The coal rock, characterized by low penetration rate and low vibration (which contradicts the correlation trend) appears to be well isolated.

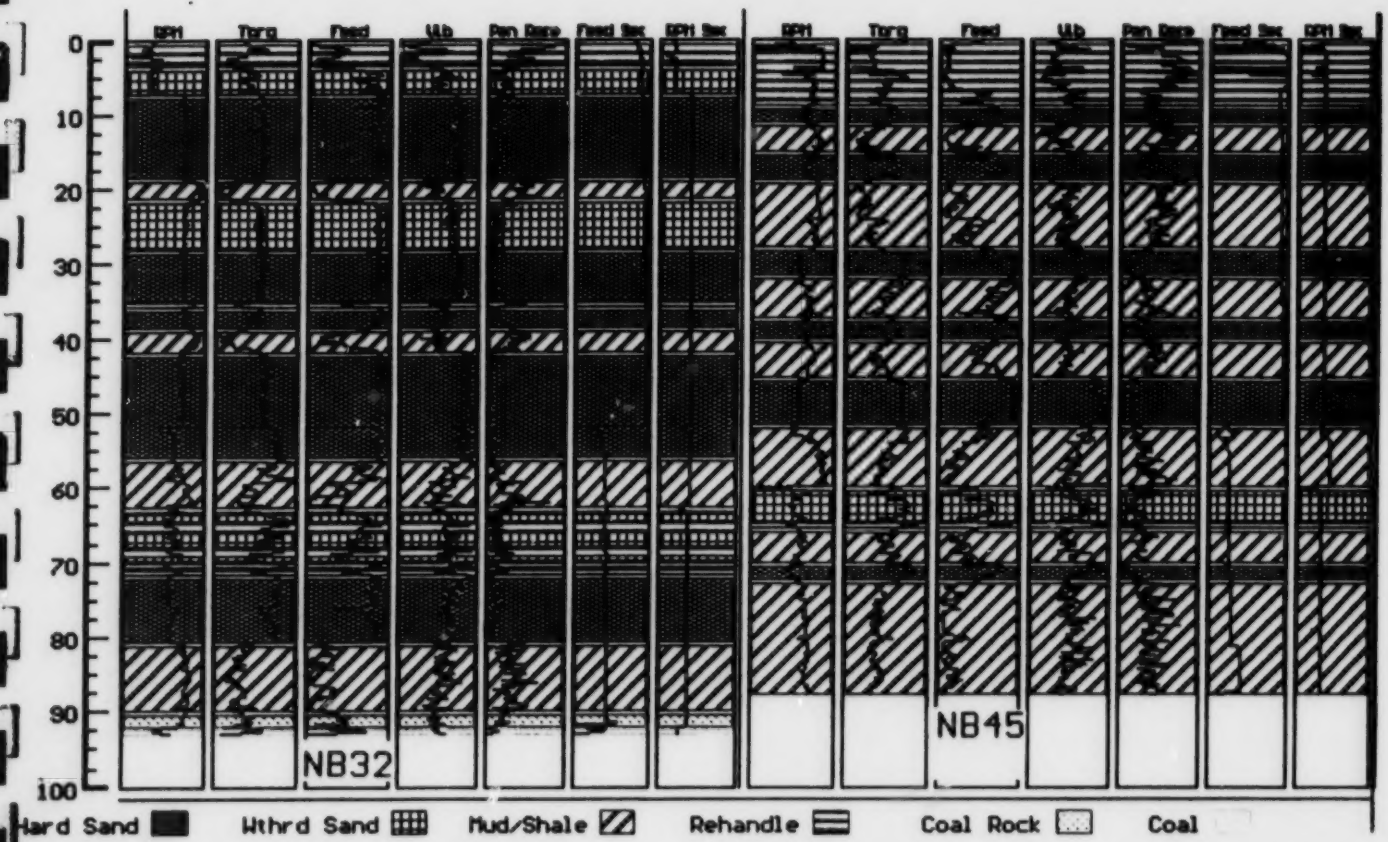


Figure 4.3 - Variation in Sandstone and Mudstone/Shale Units Along the Bench.

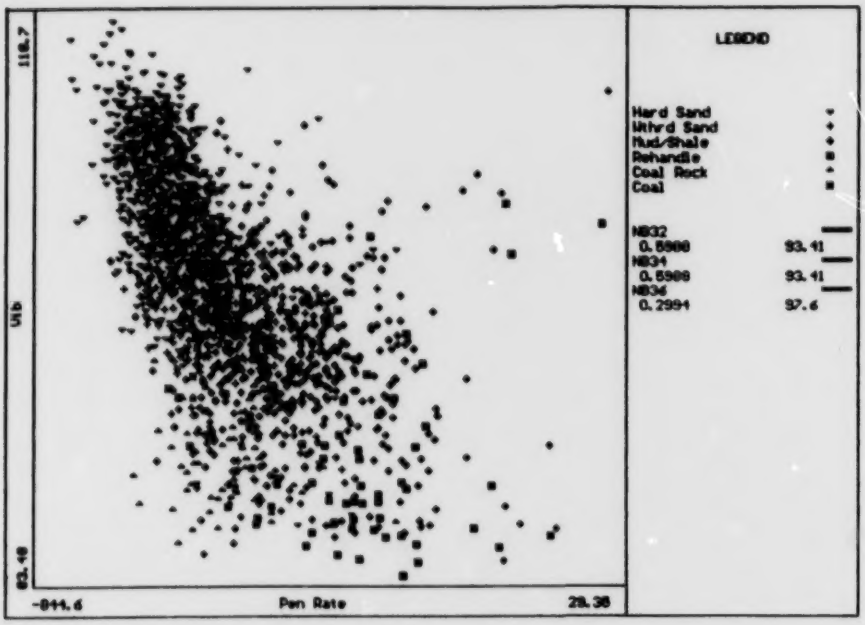


Figure 4.4 - Scatterplot of Vibration versus Penetration Rate.

Figure 4.5, a plot of torque versus vibration, shows similar relationships amongst the defined classes. Rehandle, in this case, however, is more widely scattered than before. An even greater difference is observed in terms of the relationship between hard sandstone and weathered sandstone. Considerable overlap is illustrated between these two rock units, due to a variation in the feed setpoint parameter. This variation has the effect of 'dragging' the softer weathered sandstone across what would otherwise be a hard sandstone region thereby inducing overlapping. This aspect does make it more difficult to readily distinguish hard from the weathered sandstones.

The effect of the operator is more explicitly seen in torque-RPM plane shown in figure 4.6. The plotted symbols represent the data from three boreholes and their behaviour strongly illustrates the relationship 2π(torque)*RPM = rotary power, which is constant for the

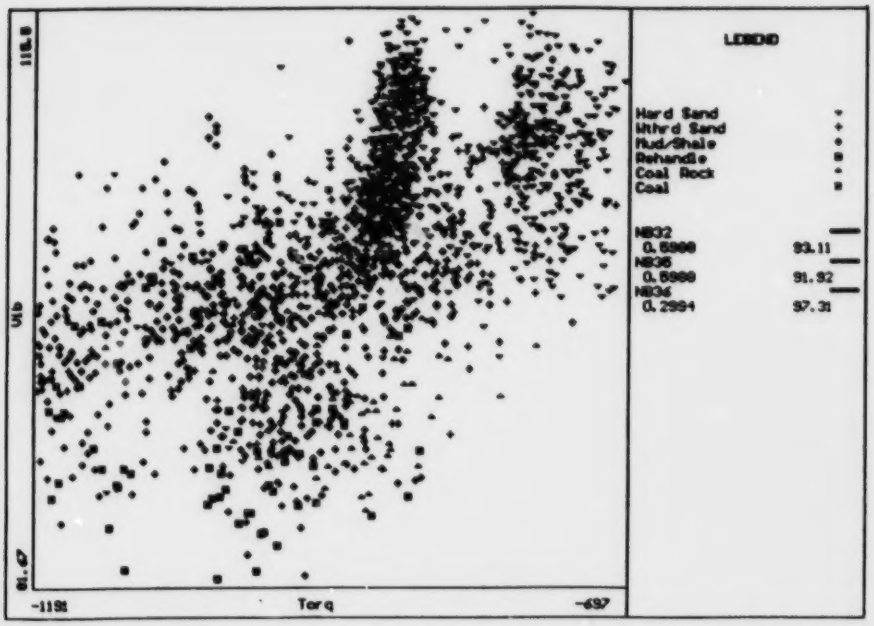


Figure 4.5 - Scatterplot of Torque versus Vibration

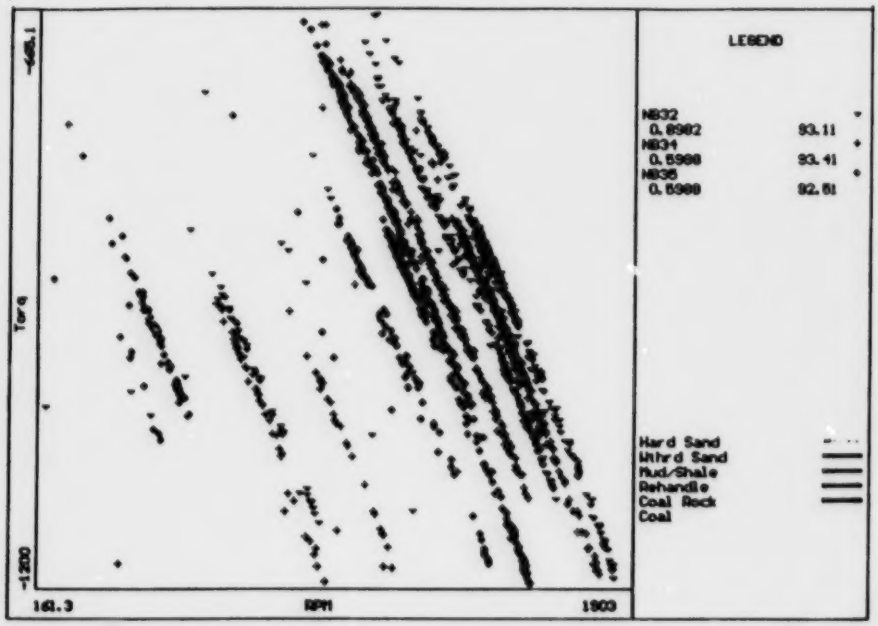


Figure 4.6 - Scatterplot of Torque versus RPM.

particular motor type. This relationship is a characteristic response of electric DC shunt motors. It has been found that the rotary power is determined from the RPM setpoints, therefore explaining why each of the 'lines' in figure 4.6 are generally composed of one symbol. Looking at the same plane but with the symbols representing the identified rock types in figure 4.7, shows that this phenomenon results in the partitioning of the class clusters into disjoint regions. Such a configuration is in general more complex and thus more difficult for a classifier to handle.

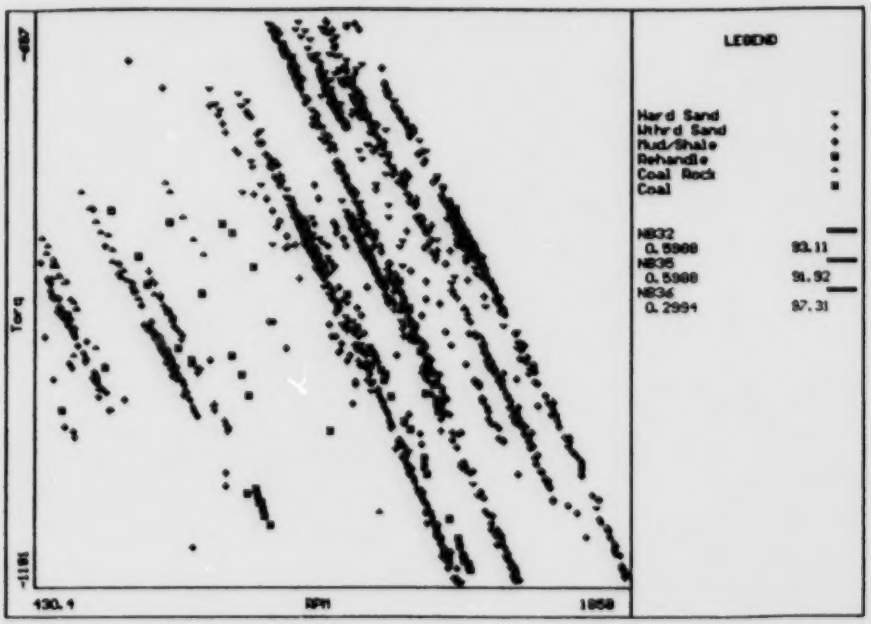


Figure 4.7 - Scatterplot of Torque versus RPM.

Figure 4.8 shows the separation of the classes in the frequency domain of the vibration signal. As was indicated by the scatterplots involving the average power of the vibration signal (figure 4.5), the harder rocks cause the rotary drill head to 'shake' more than in the softer rocks. What information cannot be captured by simply the average power is the distribution of frequency bands in which the power of the vibration signal from the classes occurs. This is most apparent with the spectrum from rehandle where the central 'peak' has been shifted to a lower band, where such a shift is suspected of being the result of a lower RPM. Other differences not discernable by average power include the tendency of the softer rocks to 'peak' more sharply than the harder rocks at about 275 Hz. While there appears to be discriminating information from this perspective in general, bands greater than 350 Hz indicate the frequency components in this range offer little in terms of discerning one rock type from another.

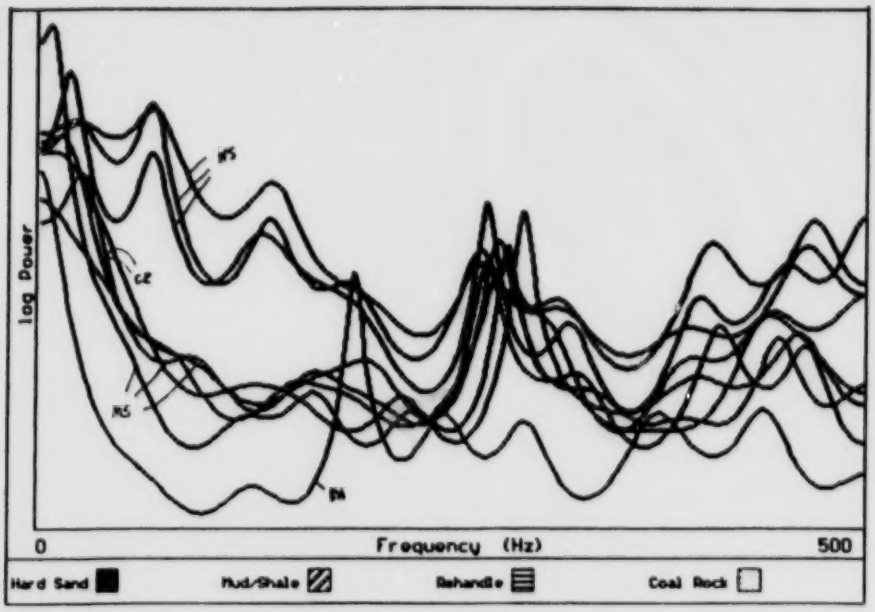


Figure 4.8 - Frequency Plot of Vibration

Therefore, it can be concluded, that the number of rock types that can be defined from all data sources is excessive for practical purposes. This fact is especially true in the case of NB Coal where the identification of only two classes, ie. "blast" or "don't blast", would suffice. However, the justification for a more comprehensive system, in which all rock types can be accurately resolved is that:

1 - the blasting objective would not allow for an adequate evaluation of the recognition techniques currently being investigated (ie. it would be too easy) and,

2 - reversion to such a basic capability is trivial once the detailed recognition framework has been proven viable.

4.5 Preliminary Experimentation and Results:

Preliminary experiments were performed in August 1991 using the drill data obtained from the two field periods. Static classification using an Artificial Neural Net (ANN) and symbol generation using a vector quantizer (VQ) were achieved with moderate success. This was done primarily to test the routines and to obtain a more focused bearing on how to proceed with more comprehensive data experimentation.

Two such classifiers were created for this experiment where the first was calibrated from the data set NB1 and the second calibrated based on the data set NB2[3]. The first classifier was used to recognize the lithology in hole NB26 while the second was used to recognize that in hole NB15. The results are shown in figure 4.9 and figure 4.10 respectively, where the actual lithology is given on the left and that recognized on the right. It can be seen that while there is some confusion with soft rocks, the hard sandstone beds, the beds of interest where blasting is concerned, stand out quite clearly. Similar results were obtained from a more comprehensive data analysis as described in subsequent sections.

[3] Each data set consists of a group of holes, ranging in number from four to nine, monitored in a single day. Each of the sets is separated by approximately ten to fifteen holes and consequently is considerably different in terms of lithology.

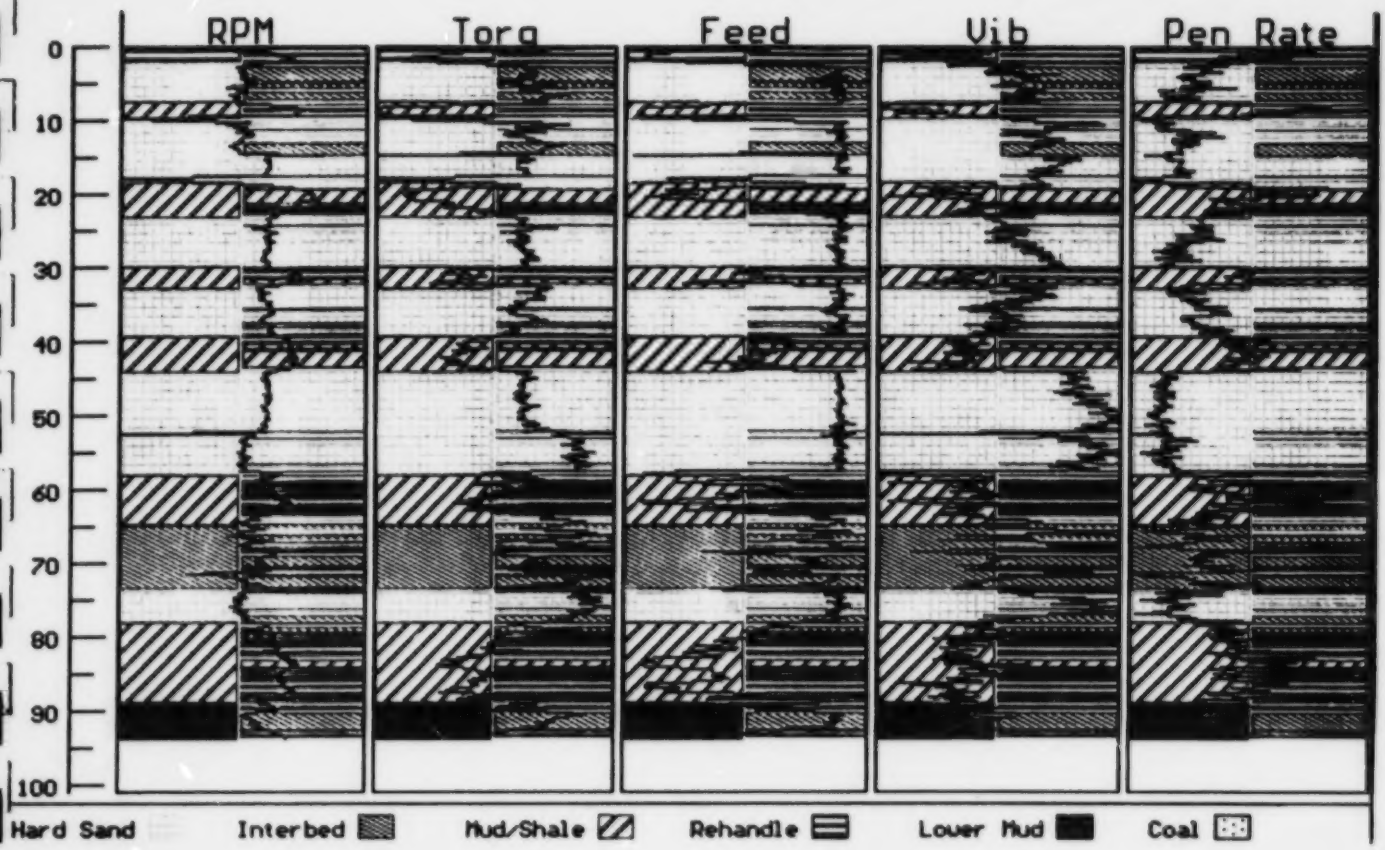


Figure 4.9 - Preliminary Recognition: Hole NB26.

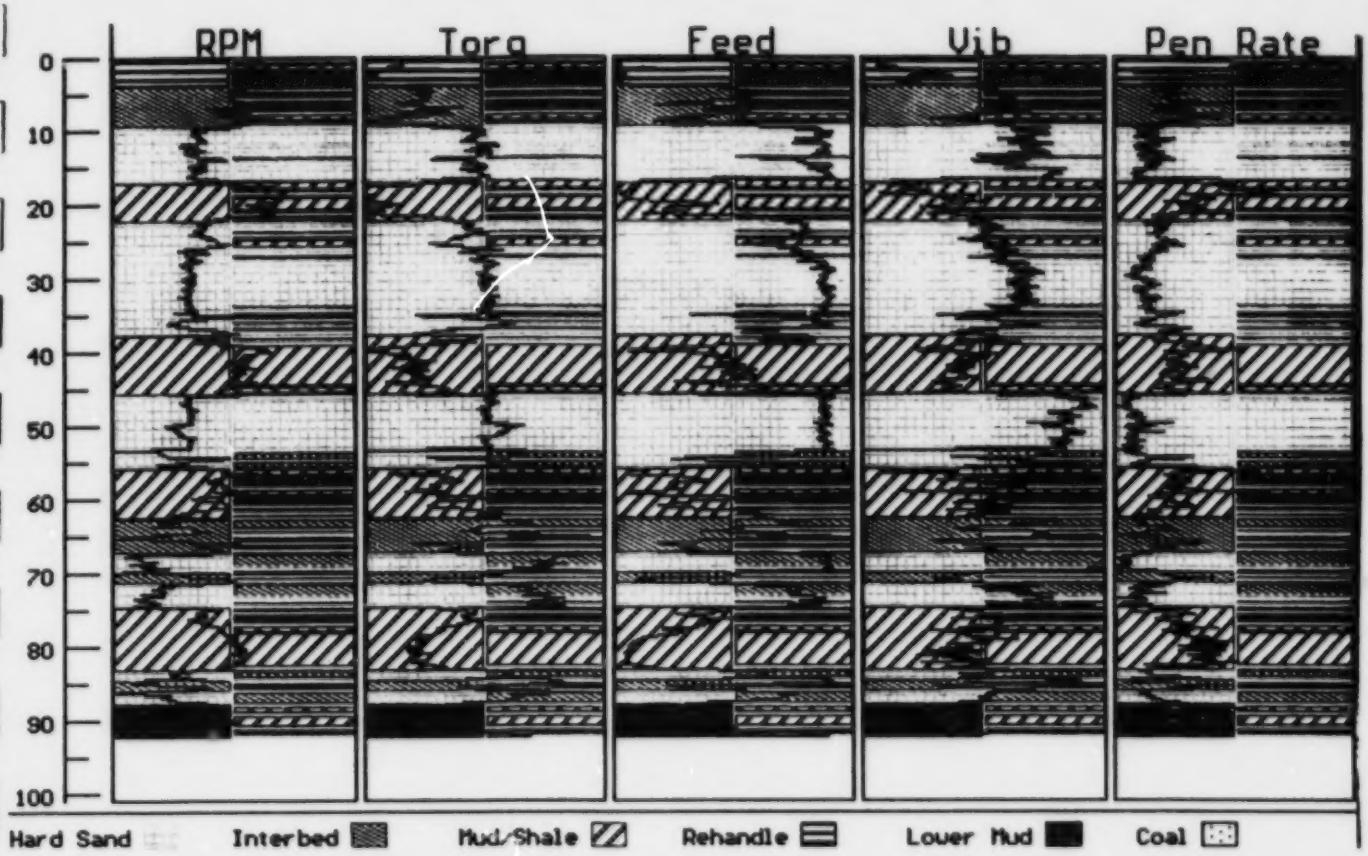


Figure 4.10 - Preliminary Recognition: Hole NB15.

5.0 DATA EXPERIMENTATION AND ANALYSIS:

5.1 Data Experimentation:

A series of experiments were performed to investigate various aspects of feature extraction methods, classifiers, the use of context and the nature of the training set. The most common measure of a recognition system's performance is its error rate (ER). While this measure will be used for these investigations, it should be noted that the absolute error rates are of little practical significance. Such figures are highly dependent on the definition of the classes - the fewer the rock types the better the performance. Instead, what are of interest are the relative error rates.

First, an experiment to estimate the sufficient number of training patterns will be discussed.

Following this, an experiment to determine the sufficient number of hidden nodes will be detailed. The effects of spectral information and various different DC input configurations are then explored. Finally, the results from the contextual algorithm CONFORM will be presented and discussed. In all, two hundred and fifty-three experiments were completed for the project. These required approximately six days of continuous computing on a 80386-based machine.

5.1.1 General Methodology

To avoid repetition, the methodology common to many of the conducted experiments will be discussed. Most of the parameters evaluated are inter-dependant, for example, the number of patterns that are needed to sufficiently train an ANN is thought to increase with the number of hidden nodes (Hertz et.al., 1991). To evaluate the combinatorial number of different configurations implied above was considered prohibitive. This situation was overcome by fixing all but one of parameters (i.e. the number of hidden nodes) which is varied and gauged. There still remains, however, the problem of determining the values at which these parameters are fixed and the extent to which any variation affects the resulting trend. To minimize any potential ambiguities, a preliminary set of 'coarse' experiments was undertaken where different combinations of widely-varying parameter values were explored. In this way a 'feel' for the data was obtained and 'default' values for untested parameters were derived. These preliminary experiments involved 20,000 ANN training iterations, with 10 hidden units and an input configuration consisting of all the DC parameters and no cepstral coefficients.

Three data sets were used as the default for training, including what may be viewed as a 'local' data set, a 'global' data set and a data set unique to the spectral information tests. The global data set is composed of data from twenty-one boreholes of groups NB1, NB2, NB4, NB5; group NB3 (seven holes) was in this case used for testing.[4] The local data set along with the third data set will be described in due course. In all three cases, however, the data used to train a static classifier was selected from specific intervals where the parameters were judged to 'typify' those of the current class. Conversely, all patterns in a borehole were used for testing.

Each of the ANN's was trained as follows: 1. One thousand patterns were randomly selected from the prescribed intervals and put into an array; 2. A pattern from each class in succession was drawn at random and shown to the net; 3. Step 2 was repeated until one

[4]Standard recognition practice dictates that a system cannot be tested on the same data with which it was trained if the resulting error rates are to be deemed credible. Further discussion on this subject is found in Toussaint et.al. (1984).

thousand patterns in total had been shown, whereupon the gain factor was decreased and control was passed back to step 1. These three steps were repeated until the desired amount of training had been achieved. Each of the boreholes were equally represented in the array as were each of the intervals (with respect to the borehole). The gain factor started at $g = 0.1$ and varied linearly with respect to the number of patterns shown to end at $g = \epsilon$, a small number.

The KNN classifier was implemented in a straightforward, exhaustive search manner. The number of nearest neighbours examined, k, was set to 30.[5]

All routines were coded in C and assembler and were implemented on a 80386-based machine.

5.1.2 Determination of the Sufficient Number of ANN Training Patterns

Before any other experiments can be undertaken with ANN's the number of training patterns beyond which recognition performance does not increase must be found.

To this end, three nets were each trained with an increasing number of patterns; this number started at 2000 and was incremented by 2000 until the three nets were trained with 20000 patterns. The default configuration was used.

The results are given in figure 5.1 where it can be seen that after 10000 patterns recognition performance does not improve. (That it appears to start to deteriorate after this point is probably not statistically significant). This amount of training is quite small when

compared to other applications such as speech where the sufficient number of patterns may be an order of magnitude greater. This indicates relatively non-descript class and unconditional distributions - the partitions separating the rock types are not inherently intricate and thus can be estimated quickly.

Variation in performance tends to be quite high when comparatively few training patterns are used. This is consistent with earlier expectations, as with a greater amount of training the probability that only portions of the respective class distributions are shown to the net is decreased.

From the point of view of implementation, these results are promising in that the

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[5]Optimal k has been shown to be equal to N[1/2] where N is the size of the training set; however, it was found (Pollitt, 1990) that increasing k beyond the value used here renders little benefit.

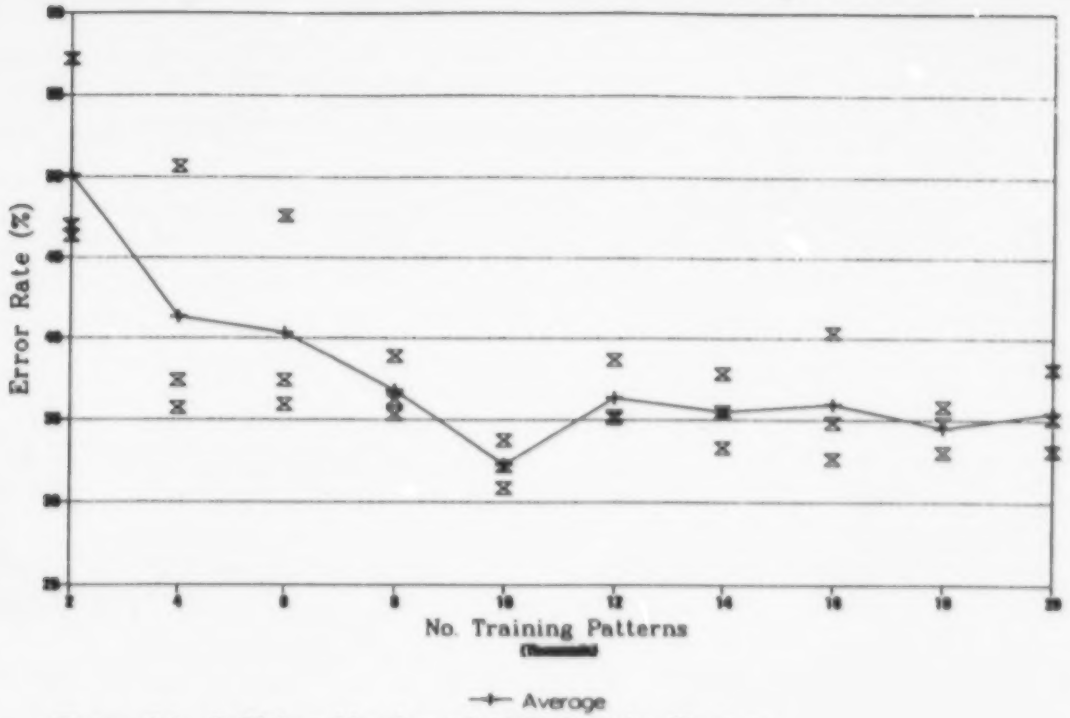

Figure 5.1 - Sufficient Number of ANN Training Patterns

connection weights can be generated quickly. However, the lack of intricacy in the boundaries signifies a considerable measure of intrinsic confusion in the data set which more sophisticated ANN configurations may not be able to overcome.

5.1.3 Determination of the Sufficient Number of Hidden Units

The other variables in the ANN were fixed at the default values while the number of hidden units was varied from 2 to 10. As in the above experiment, three nets were generated at each increment.

Figure 5.2 shows the results from this experiment. While the performance is about the same for nets with the number of hidden units ranging three to six, the variance when three and four units are used is significantly greater than for the others in the range. Therefore five or six hidden units appear to be optimal for the current application.

This is again quite a small number relative to other ANN applications, where 30 to 40 units are in some cases the norm. Because the number of these units relates to the degrees of freedom with which the partitioning function is approximated, these results corroborate those in the first experiment, namely, the data set is geometrically quite bland.

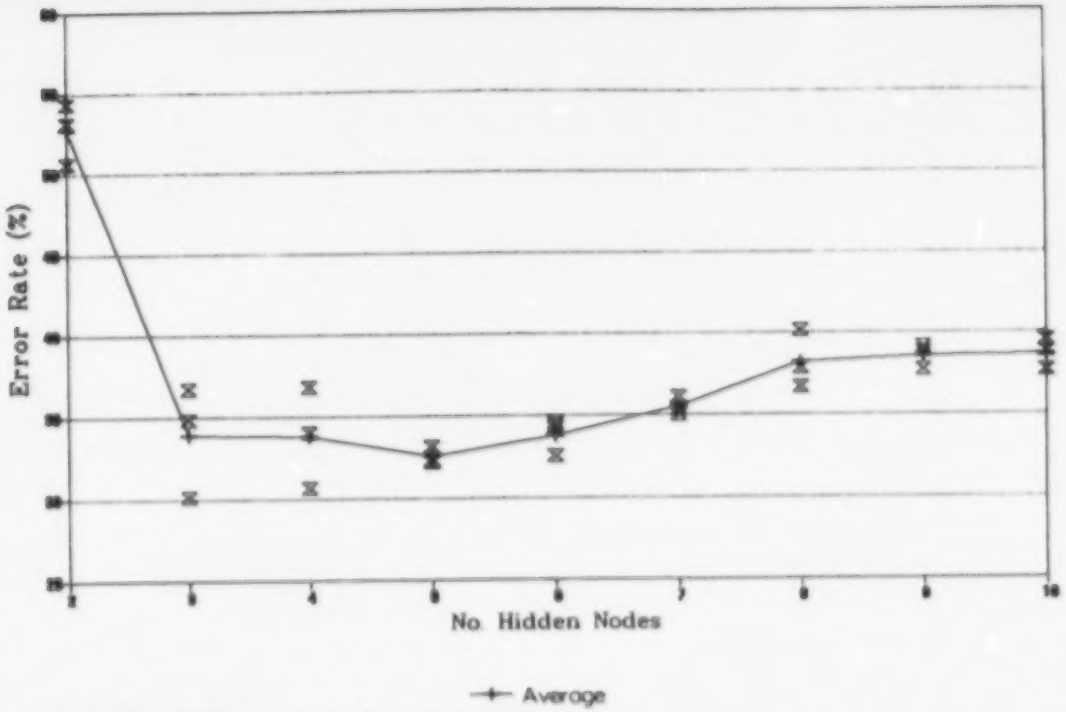

Figure 5.2 - Sufficient Number of Hidden Units

In terms of ANN implementation, what is indicated from these results, is nonetheless promising both from the point of view of necessary training and subsequent classification time.

5.1.4 The Effect of Spectral Information

The purpose of this particular experiment was to determine whether information pertaining to the frequency content of the response signals improves recognition and, if so, find the optimal AR model order. Similar experiments undertaken in the past have indicated that only such information from the vibration signal has the potential to be beneficial (Pollitt and Peck, 1991). This notion was confirmed in the present work by the qualitative analysis of the spectra from the other signals. Consequently, only the influence of cepstral coefficients derived from the vibration signal will be evaluated.

To avoid determining the appropriate parameters associated with ANNs[6], a KNN classifier was used. The data set used here is the third data set described earlier, composed of the large data set minus group NB5 and borehole NB27. The test set only differed from this data by the absence of borehole NB34. As far as the input configuration is concerned, all

[6]Because of the high dimension of the pattern vector when cepstral coefficients are used, a set of preliminary, 'coarse' experiments could not be undertaken due to time restrictions.

DC parameters were used and the number of cepstral coefficients varied from 10 to 40 in increments of 5 as it is in this range the optimal number has been previously found (Pollitt and Peck, 1991).

The results, shown in figure 5.3, indicate that including cepstral coefficients from the vibration signal is beneficial. However, the results do not indicate the appropriate model order which appears to fall somewhere between 1 and 9. That this is low compared to prior investigations may once again reflect the crude nature of the data set acquired at NB Coal.

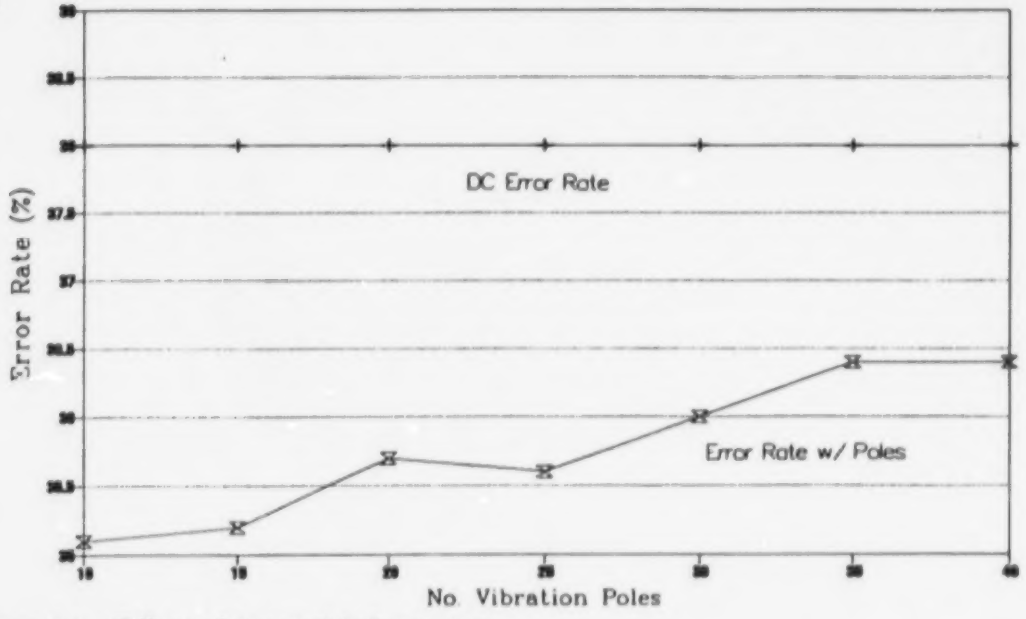

Figure 5.3 - Effect of Spectral Information

Although the positive contribution of spectral information indicated here has been affirmed elsewhere, there remains the possibility that what is seen in figure 5.3 is merely the result of more 'emphasis', in terms of components, being placed on the vibration response. The existence of this phenomenon is supported and further discussed in the next two sections.

5.1.5 DC Input Parameter Study - Large Data Set

This experiment was designed so as to examine the worth of DC input parameters and combinations thereof both in terms of ANN and KNN classifiers. The combinations were arranged to specifically investigate the affects of the RPM-Torque parameters, the setpoint parameters and the Stratalogger Plus data as compared to a configuration where all parameters are used.

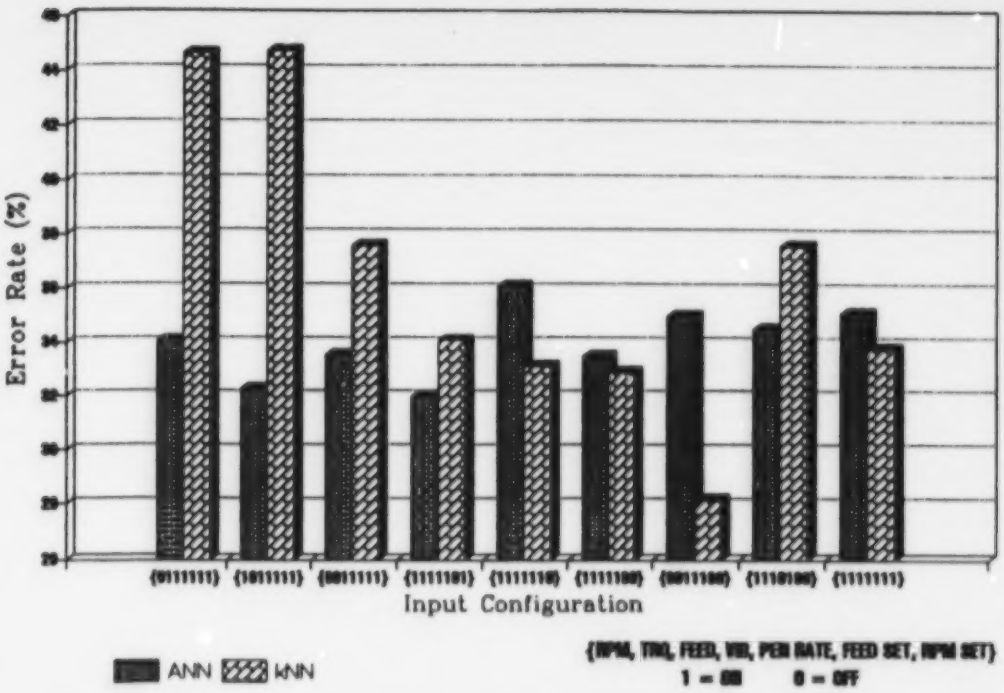

Figure 5.4 - Error Rates for Varying Input Parameter Configuration

The default settings, where applicable, were employed. Three ANNs were generated for each input configuration and the results, shown in figure 5.4, were averaged.

The first two input configurations alternatively omitted RPM and torque respectively. Because each of these parameters were seen to obey a rather strict relationship as a function of the other along with the setpoints (i.e. a great deal of redundancy existed), the exclusion of one was hypothesized to have a negligible effect on the performance. The results from the KNN classifier show this is not the case at all. While this phenomenon is not fully understood for the monitored M5 drill at present, it is suspected that the relationship alluded to above is not sufficiently borne out by the diversity, or 'smear', of the large data set. This being the case, using just one of the two parameters in this way becomes extraneous and, in terms of the KNN, simply adds a meaningless - and therefore confusing - vote to the decision making process. This explanation is supported by the fact that the ANN, which more easily adjusts to less relevant information, does not display such behaviour. Furthermore, when only vibration, penetration rate and feed are used (configuration #7), all of which, in contrast to torque and RPM, are relatively independent of the setpoints, the performance increases dramatically with the KNN.

All this suggests the other four parameters are, at best of little use to the recognition process. Figure 5.5, however, implies otherwise. Shown here is the actual lithology (left), a statically classified lithology which incorporated the RPM setpoint (middle) and a statically classified lithology which did not incorporate this parameter (right), with the RPM setpoint trace superimposed. It is clearly seen that the lack of the RPM setpoint induces the classifier to mistake an interval of coal rock as mud/shale. Obviously there is pertinent information in this signal, and by extension it may be deduced that this is also the case with the other three parameters which do not quantitatively manifest their positive contribution. The problem remains finding a means to effectively include this information.

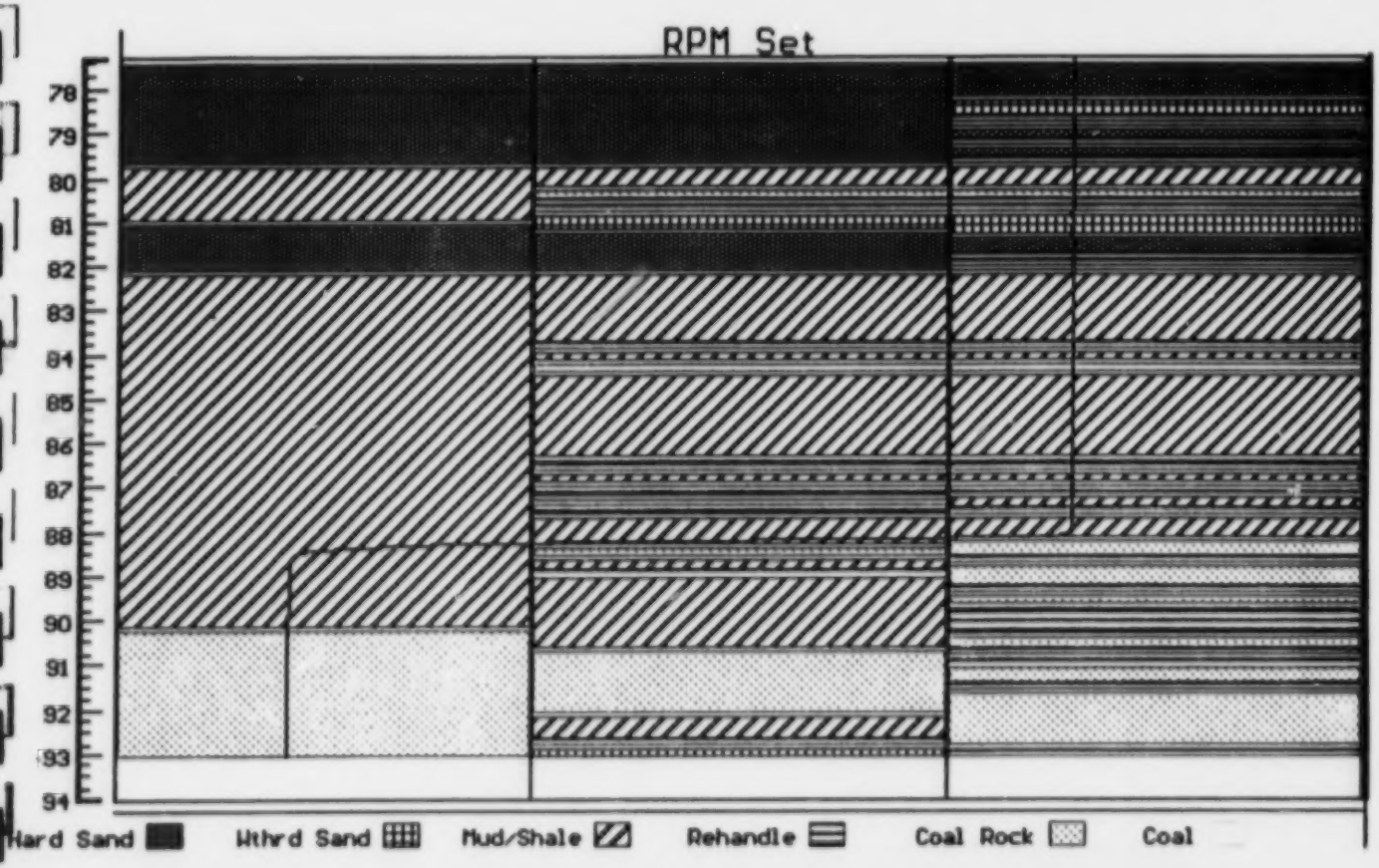

Figure 5.5 - Effect of RPM Setpoint on Static Classifier Performance

In terms of the relative merit of the two classifiers, the results shown in figure 5.4 are not decisive. It may nonetheless be concluded that in general an ANN will perform on par with the KNN and is less sensitive to the input configuration. Because of the far superior

time/space characteristics of ANNs, this may be considered favourable from a practical implementation standpoint.

5.1.6 DC Input Configuration - Small Data Set

To reduce the scatter associated with training and subsequently to test a classifier on a wide range of boreholes with the accompanying systematic variations, the above experiment was repeated with a limited data set. In this way, it was hoped that the intrinsic value of each of the DC input configurations would be made more apparent.

The 'small' data set actually consists of three training sets and three test sets, all restricted to the NB3 group. More specifically, to test boreholes NB32 and NB34, the training data consisted of all boreholes in group NB3 but these boreholes. This scheme was repeated, with the boreholes being tested left out of the training set, in order to test each of the remaining boreholes in the group. The error rate for a given input configuration was found by averaging the results for each of the three individual trials. Three ANNs were generated for each of the input configurations; the KNN classifier was not considered.

The results and the variances of the results[7] are shown in figure 5.6. The relative error rates for the configurations involving the omission of either torque, RPM or both, seem to comply with those produced when a large data set was used, whereas the error rates involving the omission of either or both of the setpoints do not. The reason for this effect cannot be explained from the current results. The configuration employing only vibration, penetration rate and feed again does well both in terms of error rate and error rate variance. The latter aspect may be due to the fact that with this arrangement there are relatively few connection weights i.e. free parameters, to estimate. Perhaps the most striking difference between the two experiments is the very large discrepancy between the results for the Stratalogger Plus configuration (#8). Here, the results show it to be by far the worst of the other 9 experiments. These results may be interpreted as indicating the importance of both the vibration and the setpoints when using either torque or RPM.

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[7]Three trials, statistically speaking, will not provide an accurate indication of the true variance; they may, however, give a hint as to what this value is.

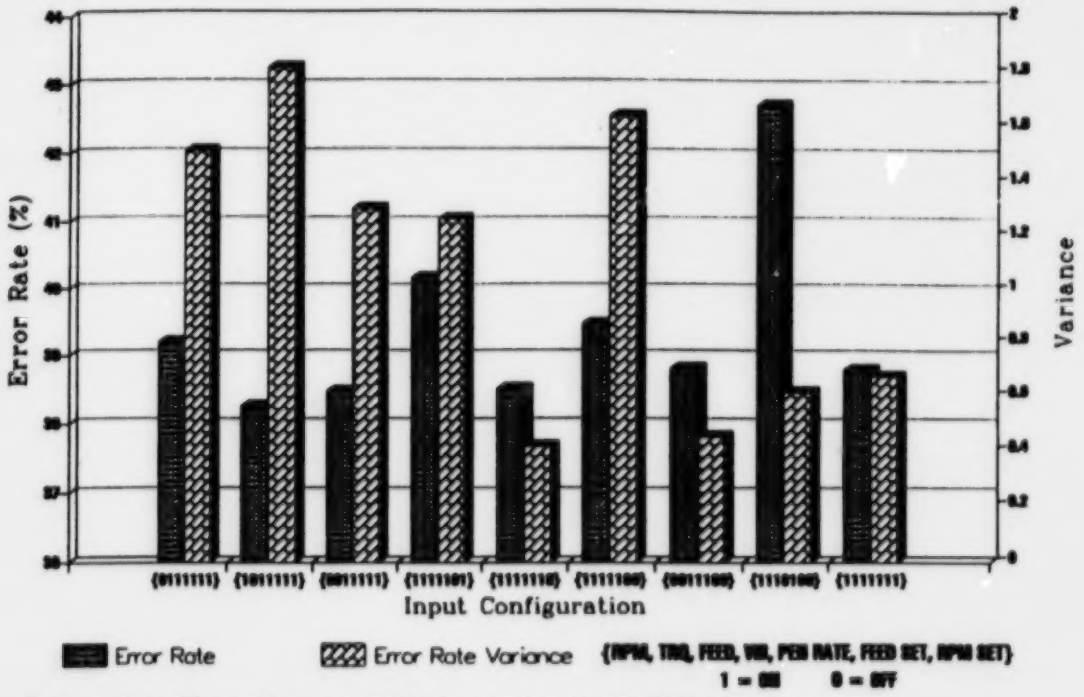

Figure 5.6 - Error Rates and Variances for Small Data Set

5.1.7 The Contribution of Contextual Information via CONFORM

A variety of aspects in regard to the incorporation of contextual information via the CONFORM algorithm are explored in this section. The most prominent of these is the extent to which this routine reduces the overall error rates. Other considerations include: the number of iterations needed to achieve the optimal performance; whether or not the routine is stable and finally the degree to which the error rates of the initial, statically classified lithologies affect the ultimate effectiveness of the technique.

To meet the objectives outlined above, a 256-word codebook was generated by means of the algorithm previously described in section 3.0 using data from all groups but NB3 which would again serve the purpose of a test set. Codebook generation involved all DC input parameters except the setpoints. Boreholes from group NB3 were encoded in a straightforward manner. The intervals used for the string matching algorithm were contiguous, non-overlapping segments of the traces approximately 2 feet in length. The free-shift factor was set to 3 feet. These parameters having been set, the experiment was conducted as follows: a set of statically classified lithologies of 'medium' performance from group NB3 were input to CONFORM. After each successive iteration the resulting lithologies were output and their error rates tabulated. This was repeated for two more sets of statically classified lithologies, one whose original error rates were 'high' and the other whose original error rates were 'low'.

The results are given in figure 5.7 from which it can be immediately seen that CONFORM dramatically improves the error rates, which in one case, the overall improvement approaches 33%. The performance does not appear to increase after four iterations and, what is most promising in terms of implementation, the process seems to be stable, i.e. the error rates do not begin to increase after the optimal number of iterations is surpassed. The results in terms of the effects of the error rates of the input lithologies are mixed: the 'high' and 'medium' lithologies resulted in near-identical ultimate error rates while the 'low' lithology maintained superiority, although by a lower margin than the originals. These results indicate that although much error-correcting can be achieved by this method, the quality of the input lithologies, and by extension the worth of the static classifier, remain important considerations.

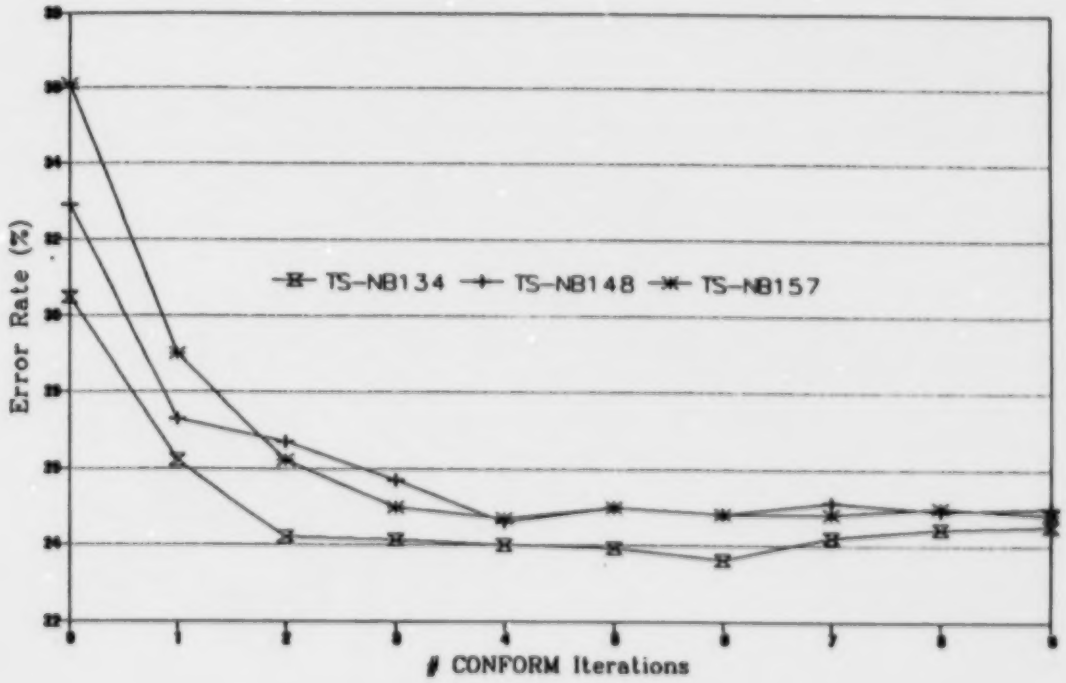

Figure 5.7 - CONFORM Iterations versus Error Rate

To illustrate the evolution of the CONFORM process, the lithologies of NB34 determined after each successive iteration are shown in figure 5.8.

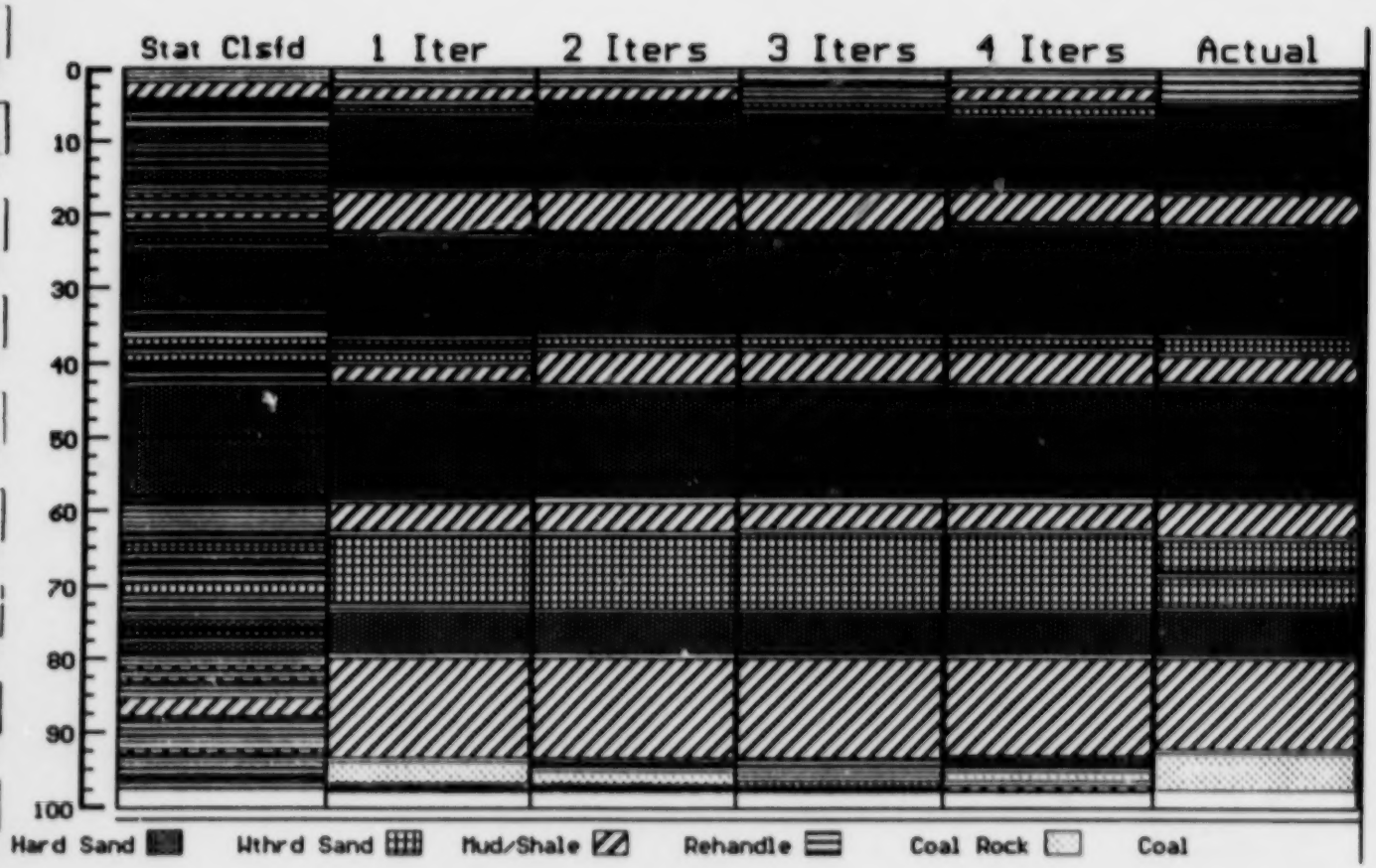

Figure 5.8 - Effects of CONFORM after 4 Iterations for NB 34.

6.0 CONCLUSIONS:

6.1 Experimental Conclusions

The following conclusions can be made in regard to the research conducted on pattern recognition techniques:

1 - Artificial Neural Nets (ANNs) performaed as well as the k Nearest Neighbor (KNN). The ANNs were less sensitive to the input configurations;

2 - For the Marion M5 at NB Coal - while the torque and rotary speed data appear to provide discriminatory information regarding the rock types, a means to properly

use these signals needs to be derived;

3 - Spectral information obtained from the drill data improves the recognition performance only slightly;

4 - Since the data set and class distributions are non-descript for the NB Coal site, the ensuing partitions are geometrically simple. These can be estimated suing an ANN of low order after relatively few training patterns;

5 - The use of Hidden Markov Models (HMMs - CONFORM) provide the bets overall results in terms of discriminating waste rocks from coal. This technique would be a major component of any implemented recognition system at NB Coal;

To translate these conclusions into more practical terms, the results have demonstrated that:

1 - It is very feasible to automatically obtain detailed bench geology based on processing monitored drill performance data using pattern recognition techniques;

2 - Using vibration, penetration rate and pulldown pressure (feed) responses, the lateral and vertical variation in sandstones, mudstones/shales and coal units can be accurately identified;

This capability is illustrated in figure 6.1. This figure illustrates the geology determined for 6 blastholes at NB Coal, based on geophysical logs (left) and using the CONFORM algorithm. It is clear that the results from CONFORM are very similar to those obtained from the interpretation of the geophysical traces.

3 - The monitored drill data can be processed rapidly to obtain meaningful and reliable results, provided that appropriate recognition techniques and hardware are used, and that the system has been calibrated for the particular site and drill.

4 - A drill monitoring system to enable such a capability as in 4, could be implemented based on additional hardware and software development. The Stratalogger Plus hardware currently installed at the mine, could be a component of the desired system.

5 - Monitoring the setpoints for pulldown pressure and rotary speed allows for the development of reliable and robust recognition software to provide good performance independent of operator adjustments to these parameters (figure 5.5);

6 - Upon a comparison of the data acquired from the CCARM-McGill DAT/PC hardware and the Stratalogger Plus, it was clear that the latter did not provide the same level of performance. This was mainly the result of this system not monitoring the vibration nor the operator setpoints. Towards making the Stratalogger Plus more effective, these variables should be monitored.

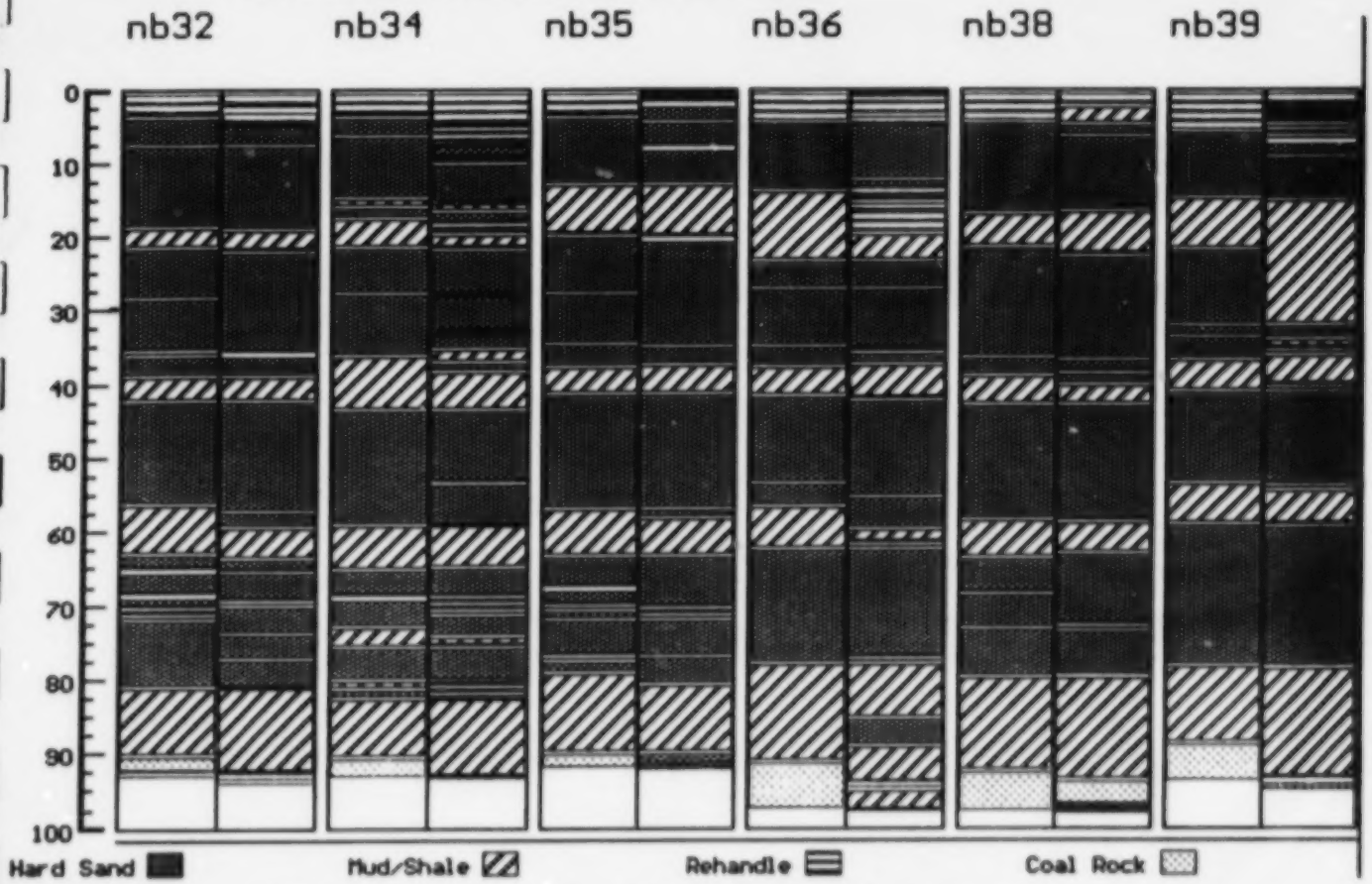

Figure 6.1 - Classified Bench using CONFORM (right-hand side).

6.2 Benefits of Drill Monitoring Technology:

The results of the completed research could lead to the eventual development of software and hardware to permit the *automated processing and interpretation of drill performance data* in real-time. This capability would permit the type, depth and thickness of the waste versus coal horizons to be identified from borehole to borehole, based solely on the responses in monitored drilling performance. At the present time, due primarily to the well-defined stratigraphy of coal mines, this technology offers the most potential for success as shown

stratigraphy of coal mines, this technology offers the most potential for success as shown in Figure 6.1.

With further research involving an examination of the relationship between drill variables and hard rock properties, the same approach could be developed for use in copper, gold and iron ore open-pit mines. In these hard rock mines, less emphasis would be placed upon the precise discrimination of different lithologic zones. What is of more importance in such cases is the identification of zones of differing relative strength or hardness. This information would be of considerable use to define explosive blends and loading requirements. The same drill data could potentially be used to define zones of varying grindability in advance of the mill, and ore grade, if relationships can be defined between drill variable response and these properties through detailed field studies. Efforts are currently being directed towards this end in Australia (BHP Central Research Labs - Iron Duke Mine) and studies are planned by CCARM-McGill in cooperation with Iron Ore Canada, Labrador City, and Highland Valley Copper, Logan Lake, B.C. in 1992.

Using an automated drill data recognition system, cost savings in open-pit coal mines would result from more accurate explosive charge placement in the blasthole based on the interpreted data. This would result in improved waste rock movement (casting) while minimizing coal dilution for reduced explosives cost. These endpoints could be achieved at a cost which is a fraction of the overall savings that would result. In addition, this data would be obtained *while drilling*, thus reducing the need for geophysical logging, while enhancing the quality of information available from more traditional sources.

The capabilities of computer-based mine planning systems presently in use in open pit coal mines, for example MEDSYSTEM from Mintec Inc., could be greatly enhanced using the interpreted drill performance data. This data could be used to precisely identify coal seam, overburden, interburden and rehandle depths and thickness across a particular bench level.

Based on either manual or automatically (optimal) interpreted drill performance logs, and data from geophysical and driller reports, a revised geological interpretation could be generated for each monitored bench level. Here, the percentages of waste to coal could be easily determined from rock unit depths and thicknesses as obtained from drill intersections - the precise determination of the bench geology is critical for production control. While short and long-term mining plans are based on limited information (diamond drilling, geophysical and driller logs, past production, etc.) only estimates are known in advance as to how much coal will be produced from a particular bench at a certain time. Revised models, based on the drill data would be of assistance during the pattern design and reserve calculation of adjacent blocks of ground. The monitoring of rotary exploration holes could also permit updates in reserve estimation and mine models on a larger scale. This

data would be further refined and upgraded when combined with the smaller scale bench models, as the latter information becomes available.

One of the most apparent and immediate benefit of an automated recognition system would be the ability to design blasts in a more efficient manner. Currently in open-pit coal mines, the interfaces between different rocks are determined from bench plans and driller's logs. In situations where these two sources of information are contradictory, gamma logging may be undertaken (if available) to confirm the true location of the interface between waste rocks and coal. However, if the gamma logging tool is not properly calibrated nor zeroed at the collar bench elevation, the data can be inaccurate. In addition, gamma logs are affected by numerous factors which can produce anomalous results, while also being time consuming, tedious and expensive. Improved coal and rock rehandle contours defined through monitored drilling would enable more precise bench plans to be generated and thus better blast designs. The responses in drilling variables have been shown at NB Coal to reflect changes in the in-situ rock strengths more precisely than gamma logs. As a result, explosives could then be blended and placed to more closely account for these variations to depth in the blasthole, leading to reduced dilution and improved scheduling of equipment based on more accurate estimates of muckpile volumes. Drill monitoring would also allow for the collection of production information on overdrilling, bit usage, drill productivity (i.e., downtime vs. actual drilling time) towards isolating overall drill costs.

In summary, the yearly savings from drill monitoring in open-pit coal mines could be related to:

- reduced geophysical logging and exploration requirements;
- reduced manpower for log interpretation and data handling;
- reduced explosives costs through optimized loading.

Additional cost savings could also be due to enhancing the geological data from traditional sources to provide:

- more consistent thickness and depth interpretation of coal seams;
- increased resolution in identifying partings and minor coal seams;
- increased hole densities for building geologic models, thus increasing the accuracy of coal volume predictions;
- improved fragmentation and thus better digging conditions;
- lower blast vibrations due to proper charge placement.

6.3 Recommendations for Future Work:

6.3.1 Drill Monitoring Systems

Several options are proposed towards developing and implementing a complete drill monitoring system at NB Coal. The first option or off-line monitoring, would be the easiest approach. This would involve the modification of the existing Stratalogger Plus hardware to also acquire vibration and setpoint data. As is the current situation, an NB Coal employee would board the drill at regular intervals to off-load the monitored data via a laptop computer. This data would then be downloaded to a PC computer in the mine office, where software (to be developed) would process these using the recognition algorithms described in this report. This computer would contain the necessary hardware (DSP - digital signal processor board) to implement these algorithms. The resulting data could be sent to a computer screen or printer to illustrate the defined geology per borehole in a graphical manner. Also, this same information in numerical format, could be transferred into existing planning software (eg. MEDSYSTEM) for use in other mine applications.

Additional data downloading options for the off-line approach include the use of RAM cards (can store up to 1 Megabyte of data) and radio or modem links. For the first option, which is relatively inexpensive, the drill operator would insert the RAM card at the beginning of his shift. Upon completion of his shift, the data would have ben downloaded to the card, which the operator then removes and hands it to his shift boss. The shift boss is then responsible to drop the RAM card at the mine office for processing. The data would be downloaded to the mine office PC computer in a similar fashion as for the laptop computer. The RAM card option will be available from Thunderbird Pacific in January 1992.

Another possibility is the remote transmission of the drill data via radio or modem. In either of these cases, the data could be automatically downloaded at pre-defined intervals of time to the mine office PC without human intervention. This facility would eliminate any need for a physical data transfer. A radio link interface to a Stratalogger Plus has been operating successfully at Quebec Cartier Mines, Mt. Wright mine since October 1991. A modem link could also be used to accomplish the same task as the radio. Using a cellular telephone installed on the drill, this option would be less expensive and require less development time and no licensing as compared to a radio link.

An on-line, real-time drill monitoring recognition system is the ultimate objective for particular open-pit coal mines where drilling and loading operations are very closely spaced in time. This approach would require considerable hardware and software development.

Such a system would permit the viewing on a computer screen in the mine office (on the drill?) the geology that is being drilled in real-time. To achieve this capability, additional hardware would have to be developed which processes the raw drill data acquired from a monitor using the recognition algorithms, on-board the drill. This compressed data set, which would consist simply of the hole number, and the depths and types of rocks recognized, could be easily transmitted in real-time via a radio/modem link to the mine office. The incoming data could be sent to a screen or printer for immediate use. The additional hardware required on-board the drill would consist of DSP and PC-386 computer boards in a ruggedized box interfaced to the appropriate communication device. The hardware would be essentially the same configuration as required for the off-line approach described earlier, but would be on the drill and not in the mine office.

Therefore, a project to develop any of the outlined drill monitoring options is proposed. Based on the direction that NB Coal would like to follow, a proposal outlining the objectives, tasks, milestones, deliverables, execution plan and costs would be submitted to the mine by CCARM-McGill within the next 1 to 2 months.

6.3.2 Dragline Diggability Studies

The drill monitoring systems discussed above could assist the mine to better define geology and thus design their blasts accordingly. The implications of such an approach are the possibility of improved fragmentation and reduced explosives costs. In order to provide some means of measuring the effectiveness of a particular blast, instrumentation to monitor the performance of the Marion 8200 dragline is proposed. In this manner, while monitoring certain critical parameters, a diggability index could be derived from the data which provides an indication of the degree of effort required to dig the muckpile. If an "easy" digging index is determined ie. the dragline is working within its designed performance threshold, then fragmentation and thus the blast design used can be considered good. However, if "hard" digging is encountered, as reflected by monitored parameters being in excess of "normal" levels, then the next blast would be modified (based on data from the drill) to hopefully improve the size and looseness of the muck. Hard digging is undesirable from the perspective of reduced production and increased wear and tear of the dragline through the handling of oversize, tight muck and hard toe. Through the field monitoring of dragline performance and a correlation of these responses to the fragmentation size distribution and blast design criteria, a range of diggability indices could be derived for NB Coal. As such, these studies would seek to determine the "optimal" diggability index to strive for, such that a balance is found between the blast design and desired fragmentation

size towards minimizing dragline downtime and maximizing productivity[8].

Monitoring the dragline in parallel to the drill would provide an excellent facility from which to increase the overall mine productivity through improved equipment utilization. Addition savings would result from decreased maintenance and explosives costs.

A project to monitor dragline performance is thus proposed to NB Coal. Over the next 1 to 2 months, and based upon further discussions with the mine, CCARM-McGill would submit a proposal for work which outlines objectives, tasks, milestones, deliverables, execution plan and costs to undertake this work.

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- Mr. G. Flammia, MIT, Boston, Mass.
- Mr. A. Trossman, CCARM-McGill, Montreal.
- Dr. C. Hendricks, CCARM-McGill, Montreal.
- Mr. R. Danell, BHP-CRL, Newcastle, Australia.

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[8] Similar studies were conducted by CCARM-McGill at Fording Coal, using instrumentation on-board electric cable shovels to monitor their performance. Results of this work are provided in Scoble et.al., (1989).

8.0 INTELLECTUAL PROPERTY:

The work discussed in this report is based upon existing technology developed previously during field trials at the Fording River Mine, Elkford B.C. (1987 to 1989) and data acquired during monitoring at the Delta Mine, Marion Illinois (1990). The aim of the current project was to *refine* the developed techniques in terms of their mathematical basis using drill data monitored from the Minto Mine, NB Coal.

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